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asfer (/p/asfer/)

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[r2012] (/p/asfer/code/2012/): ↗ (/../) / asfer-docs/AstroInferDesign.txt

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11417 lines (9736 with data), 1.4 MB

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1  -----
2  #ASFER - Software for Mining Large Datasets
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5  #the Free Software Foundation, either version 3 of the License, or
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16 #Ph: 9791499106, 9003082186
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18 #http://sourceforge.net/users/ka_shrinivaasan,
19 #https://github.com/shrinivaasanka,
20 #https://www.openhub.net/accounts/ka_shrinivaasan
21 #Personal website(research): https://sites.google.com/site/kuja27/
22 #emails: ka.shrinivaasan@gmail.com, shrinivas.kannan@gmail.com,
23 #kashrinivaasan@live.com
24 #-----
25
26 -----
27 NeuronRain - Design Objectives
28 -----
29 NeuronRain OS is machine learning, cloud primitives enriched linux-kernel fork-off with applications in Internet-of-T
30 the machine learning side of it to learn analytics variables later read as config by linux kernel and any device spec
31 NeuronRain has been partitioned into components so that effective decoupling is achieved e.g Linux kernel can be real
32
33
34 Copyright attributions for other open source products dependencies:
35 -----
36 1.Maitreya's Dreams - http://www.saravali.de (some bugs were fixed locally in degree computation of textual display n
37 2.SVMLight - http://svmlight.joachims.org/
38 3.BioPython and ClustalOmega Multiple Sequence Alignment BioInformatics Tools (www.biopython.org, www.ebi.ac.uk/Tools
39
40 -----
41 Open Source Design and Academic Research Notes have been uploaded to http://sourceforge.net/projects/acadpdrafts/file
42
43 Presently a complete string sequence mining subsystem and classification algorithms with indexing have been implement
44 ****
45 AstroInfer Classifiers - Documentation on the dataset files used
46 ****
47
48 decisiontree-attrvalues.txt - Attributes based on which decision is done and the values they can take (comma separate
49 decisiontree-test.txt - Test dataset with set of values for attributes in each line
50 decisiontree-training.txt - Training dataset with set of values for attributes and class it belongs in each line
51 test-set.txt - List of article id(s) to be classified - NaiveBayes
52 topics.txt - List of classes the article id(s) in training set belong to - NaiveBayes
53 training-set.txt - List of articles id(s) already classified - training dataset for NaiveBayes
54 word-frequency.txt - Words and their frequencies of occurrence in all articles - NaiveBayes
55 words.txt - words, the article id(s) having those words and number of occurrences of those words within specific arti
56
57 Above XXX.txt files need to be populated after doing some preprocessing of the articles to be classified. Preprocessi

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58 Python script for autogenerated above txt files has been added under python-src/autogen_classifier_dataset.This scri
59 ****
60 ****DESIGN NOTES, THEORETICAL INTERLUDES(might have errors), TODO AND NICE TO HAVE FEATURES (list is quite dynamic and mi
61 ****
62 ****
63 ****
64 ****
65 (FEATURE - DONE-MDL,Entropy,Edit Distance,Compressed Sensing) 1. Test with Massive Data Sets of encoded strings for p
66 ****
67 (FEATURE - THEORY-POC Implementation-DONE) 2. An experimental text compression algorithm that deletes vowels and stor
68 x1-----x2-----x3-----x4
69 | | | |
70 t h - t
71 and Bayesian for the above is:
72 Pr(x3/[t,h,-,t]) is directly proportional to Pr(x3/[t,h]) * Pr([t]/x3)
73 and to be precise it is:
74 Pr(x3/[t,h,-,t]) = Pr(x3/[t,h]) * Pr([t]/x3) / Pr(t)/Pr(t,h) with denominator being a pre-computable constant
75
76 Viterbi path would give the most likely path or most likely word for above.
77
78 (2.1) Pr(x3/[t,h]) is computed from dictionary - number of words having the sequence / total number of words
79 which is the argmax( Pr(a/t,h), Pr(e/t,h), Pr(i/t,h), Pr(o/t,h), Pr(u/t,h)) and priors are computed for the substring
80
81 (2.2) Pr(t/x3) is computed from dictionary similar to the previous for argmax of probabilities for substrings at, et,
82
83 (2.3) If total number words in dictionary is E (could be 200000 to 300000) and yi is the number of words of length i,
84
85 (2.4) Number of substrings of an n bit word is (n-1)n/2.
86
87 (2.5) Thus number of substrings for all words in dictionary is y2 + 3*y3 + 6*y4 + 10*y5 + ... + (n-1)n*yn/2. Thus num
88
89 (2.6) Above is theoretical basis only implementation of which needs precomputing the above hashtable.
90
91 (2.7) Above experimental compression scheme that ignores vowels gives a string complexity measure (a minimum descript
92
93 (2.8) Algebraically, above can be imagined as a Group Action where group G is set of consonants (with the assumption
94
95 (2.9) Linguistic words can be construed as a polynomial graph plotted on an x-y axis: x-axis represents position of a
96
97 (2.10) From point 345 and 347, high level language texts like English, French etc., can be thought of as 255-coloring
98
99 (2.11) Monochromatic arithmetic progressions in letter positions of natural language texts implies that finite state
100 a---b---a---a--->b
101 |<-----|
102
103 (2.12) In terms of vowelless string complexity measure previously, if a 255-colored string is simplified to 2-colored
104
105 3. (FEATURE - THEORY - Pairwise LCS implementation DONE) KMeans, KNN and other clustering and classification algorith
106
107 4. (FEATURE - DONE) Implementation of String Distance measure using different distance measures (python-src/StringMat
108
109 5. (FEATURE - DONE) Construct a Hidden Markov Model with State transitions and Observations(events). If the number of
110
111 6. (FEATURE - DONE - continuation of point 3) Correlate with Rules from Classics (BPHS, BJ etc.,) with the mined data
112
113 7. (FEATURE - DONE) Integrate Classifiers in above String Pattern mining (classify strings and then mine).
114
115 8. (FEATURE - DONE) At present fundamental algorithms like - Perceptrons with Gradient Descent, Linear and Logistic F
116
117 9. (FEATURE - DONE) InterviewAlgorithm code in https://sourceforge.net/p/asfer/code/146/tree/python-src/InterviewAlg
118
119 [Disclaimer and Caveat: Due to radical conclusions that are derivable from the P(good) binomial coefficients summatic
120
121 There are zero error voting systems:
122 E.g Paxos protocol without byzantine failures - http://research.microsoft.com/en-us/um/people/lamport/pubs/paxos-simp
123 ]
124 -----
125 Psuedorandom Choice and Majority Voting (Majority circuit with SAT inputs)
126 -----
127 10. (THEORY) https://sites.google.com/site/kuja27/ImplicationRandomGraphConvexHullsAndPerfectVoterProblem\_2014-01-11.
128
129 Additional References:
130 -----
131 10.1. Social Choice Theory, Arrow's Theorem and Boolean functions - http://www.ma.huji.ac.il/~kalai/CHAOS.pdf
132 10.2. http://www.project-syndicate.org/commentary/kenneth-arrow-impossibility-theorem-social-welfare-by-amartya-sen-2
133 10.3. Real life illustration of Arrow's Theorem - http://www.nytimes.com/2016/05/09/upshot/unusual-flavor-of-gop-prin
134 10.4. How hard is it to control elections [BartholdiToveyTrick] - http://www.sciencedirect.com/science/article/pii/00
135 10.5. How hard is it to control elections with tiebreaker [MatteiNarodyskaWalsh] - https://arxiv.org/pdf/1304.6174.pdf
136
137
138 11.(THEORY) What is perplexing is the fact that this seems to contravene guarantee of unique restricted partitions de

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139
140 12. (THEORY) Moreover Arrow's theorem for 3 candidate condorcet election implies a non-zero probability of error in vc
141
142 13. (THEORY) But it is not known that if Arrow's theorem can be generalized for infinite number of candidates as above
143
144 14. (THEORY) Each Voter has a k-SAT circuit which is input to Majority circuit. k-SAT can be reduced to 3-SAT (not 2-S
145
146 For example, a term in the binomial summation becomes:
147  $mC(n+1) * (1/q^s)^{n+1} * (1-1/q^s)^{m-n-1}$  where m is total number of voter SATs and  $(1/q)$  is probability of single
148
149 The Voter SAT circuit has an interesting application of Hastad's Switching Lemma - random probabilistic setting of va
150
151 As done in the Switching Lemma proof, parity circuit can be an AND of ORs (or OR of ANDs) which is randomly restricte
152
153 Fourier expansion of the unbounded fan-in Majority+SAT circuit is obtained from indicator polynomial (http://www.con
154
155 Demarcation of linear and exponential sized circuits: P(good) RHS has Circuit SAT for each voter with unbounded fanin.
156 1) If the variables for each voter SAT are same, then the circuit size is exponential in number of variables - DC-uni
157 2) else if the variables are different for each SAT, then the circuit is linear in number of variables - polynomial s
158
159 1) is more likely than 2) if lot of variables among voters are common.
160
161 There are three possibilities
162 Circuit lies between 1) and 2) - some variables are common across voters - kind of super-polynomial and sub-exponenti
163 Circuit is 1) - all variables are common across voters - the worst case exponential (or even ackermann function?)
164 Circuit is 2) - there are no common variables
165
166 As an alternative formulation, LHS of the P(Good) series can be a dictator boolean function (property testing algorit
167
168 Influence of a variable i in a boolean function is Probability[f(x) != f(x with i-th bit flipped)]. For Majority func
169
170
171 As done for sensitivity previously, a term in the P(Good) binomial summation becomes:
172  $mC(n+1) * \text{product\_of\_n+1\_}(\text{NoiseSensitivityOfVoterSAT}(i)) * \text{product\_of\_m-n-1\_}(1-\text{NoiseSensitivityOfVoterSAT}(i))$  where m
173
174 Summation of binomial coefficients in RHS is the collective stability or noise in the infinite majority circuit. It c
175
176 -----
177 P(Good) summation is Complementary Cumulative Binomial Distribution Function (or) Survival Function
178 -----
179 Goodness Probability of an elected choice is derived in https://sites.google.com/site/kuja27/CircuitForComputingError
180
181 A plausible proof for the assumption that for an above average good choice atleast half of the popluation must have m
182 If there are n inputs to the Majority circuits, the voter inputs with good decision can be termed as "Noiseless" and
183  $\lim_{n \rightarrow \infty} \text{NS}(\delta, \text{Majority}(n)) = 1/\pi * \arccos(1-2\delta)$  (due to Central Limit Theorem and Sheppard's Formula)
184 n odd
185
186 where delta is probability of noise and hence bad decision. If delta is assumed to be 0.5 for each voter (each voter
187  $1/\pi * \arccos(1-1) = 1/\pi * \pi/2 = 1/2$  which is the Noise (Goodness or Badness) of the majority circuit as a
188 From this expected number of bad decision voters can be deduced as  $E(x) = x*p(x) = 0.5 * n = n/2$  (halfway mark)
189
190 Above is infact a simpler proof for P(Good) without any binomial summation series for delta=0.5. In other words the n
191
192 For delta=0.5, NoiseSensitivity of infinite majority=0.5 and both are equal. For other values of delta this is not th
193
194 delta=0.3333...:
195 -----
196 NS =  $1/\pi * \arccos(1 - 2*0.333...) = 0.3918$ 
197
198 delta=0.25:
199 -----
200 NS =  $1/\pi * \arccos(1-2*0.25) = 0.333...$ 
201
202 -----
203 Chernoff upper tail bound
204 -----
205 Upper bound for P(Good) binomial distribution can be derived from Chernoff bound (assuming Central Limit Theorem appl
206  $P[X > (1+\delta)\mu] < \{e^{\delta}/(1+\delta)^{(1+\delta)}\}^n$ 
207 Total population is n, mean=n*p and  $(1+\delta)\mu = n/2$ 
208 Thus  $\delta = (1 - 2*p)/2*p$ 
209  $P[X > n/2] < \{e^{(1-2p)/p}/(1/2p)^{(1/2p)}\} = \{e^{(1-2p)n} * (2p)^{(1/2p)}\}$ 
210
211 When  $p=0.5$  ,  $P[X > n/2] < 1$  which is an upperbound for 0.5.
212 But intriguingly for  $p=1$  the upper tail bound is:
213  $(e^{(-1)*\sqrt{2}})^n$ 
214 which is increasingly less than 1 for high values of n whereas P(good) converges to 1 in exact case (why are these di
215  $mC(n+1)(p)^{n+1}(1-p)^{m-n-1} + mC(n+2)(p)^{n+2}(1-p)^{m-n-2} + \dots + mCm(p)^m(1-p)^{m-m}$ 
216 all the terms vanish by zero multiplication except  $mCm(p)^m(1-p)^m$  which becomes:
217  $mCm*1*0^0$ 
218 and by convention,  $0^0 = 1$ , thereby converging to 1 while the Chernoff upper tail bound decreases with n.
219

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301 Alternatively if subset of voters reveal their votes (1 or 0) in opinion polls then the above becomes a Learning Thec
302
303 An interesting parallel to election approximation is to sample fourier spectrum of boolean functions of a complexity
304
305 Points (53.1) and (53.2) define a Judge Boolean Function with TQBF example that is PSPACE-complete. Each voter in RHS
306
307 -----
308 (*IMPORTANT*) Boolean Function Composition (BFC) and Majority+SAT voting circuit
309 -----
310 Boolean Function Composition is described in detail at [AvishayTal] Section 2.3 - http://eccc.hpi-web.de/report/2012/
311
312 [
313 Quoting Corollary 6.2 in http://eccc.hpi-web.de/report/2012/163/ for inclusions of complexity measures:
314     "... C(f) <= D(F) <= bs(f) <= deg(f) <= deg(f)^3 ..."
315 ]
316
317 -----
318 Noise Sensitivity and Probability of Goodness in P(Good) LHS and RHS - Elaboration on previous
319
320 LHS of P(Good):
321 -----
322 (1) Depends either on a natural (pseudo)random process or a Dictator Boolean Function that unilaterally decides outcome
323
324 (2) When error is zero, probability of good decision is 1 (or)  $\Pr(f(x) \neq f(y))$  is zero where x and y are correlated
325 a bit flip. In other words Noise in input does not alter outcome. If NS is Noise Sensitivity, probability of good outcome
326
327 RHS of P(Good):
328 -----
329 (1) Depends on the Noise Sensitivity of Boolean Function Composition -  $\text{Maj}(n)*\text{SAT} - \text{Maj}_n(\text{SAT}_1, \text{SAT}_2, \dots, \text{SAT}_n)$ .
330
331 (2) When error is zero, probability of good decision is 1 because  $nCn*(1)^n * (1-1)^0$  becomes 1 in summation and all
332
333 (3) NoiseSensitivity is a fitting measure for voter error or voting error as it estimates the probability of how a random
334
335 (4) Perfect Voter has a SAT or Boolean Function that is completely resilient to correlation i.e  $\Pr(f(x) \neq f(y)) = 0$ .
336
337 (5) Brute Force exponential algorithm to find perfect voter is by property testing:
338     - For  $2^n$  bit strings find correlation pairs with random flips -  $2^n * (2^n - 1)$  such pairs are possible.
339     - Test  $\Pr(f(x) \neq f(y))$ 
340     - This is not a learning algorithm.
341
342 (6) For perfect voter, probability p of good decision is  $1-NS$  or  $1/2+1/2*Stability$  and has to be 1 which makes  $NS=0$  a
343
344 (7) Open Question: Is there a learning algorithm that outputs a Perfect Voter Decision Boolean Function f such that  $N$ 
345
346 Is there some other function stabler than stablest - answer has to be no - But there is an open "Majority is the Least
347 For Linear Threshold Functions (majority, weighted majority et al) f,  $\text{Stability}(f) \geq \text{Stability}(\text{Maj}_n)$ .
348 Majority is Stablest theorem is for small-influence LTFs (maximum influence of f < epsilon). If existence of perfect
349
350 An obvious corollary is that for stablest voting boolean function, majority is apt choice (or) in the Majority voting
351
352 (8) Theorem 2.45 in http://analysisofbooleanfunctions.org/ is important which proves Stability and NoiseSensitivity i
353     lt (n->infinity, n odd)  $\text{Stability}[\text{Maj}_n] = 2/\pi \arcsin(\rho)$ 
354     (or)
355     lt (n->infinity, n odd)  $\text{NS}[\delta, \text{Maj}_n] = 2/\pi \delta + O(\delta^{1.5})$  where delta is the probability of correlation
356
357 (9) There are two random variables  $f(x)=f(y)$  and  $f(x) \neq f(y)$  with respective probabilities.
358
359 (10) This implies for infinite electorate, error probability is (an error that causes x to become y with probability
360     lt (n->infinity, n odd)  $\text{NS}[\delta, \text{Maj}_n] = 2/\pi \delta + O(\delta^{1.5})$  where delta is the probability of correlation
361
362 (11) probability of good outcome =  $p = 1-NS$ :
363      $p = 1 - \text{lt} (n->infinity, n odd) \text{NS}[\delta, \text{Maj}_n] = 1 - 2/\pi \delta - O(\delta^{1.5})$ .
364
365 (12) If delta = 1:
366     lt (n->infinity, n odd)  $\text{NS}[\delta, \text{Maj}_n] = 2/\pi + O(1)$ .
367     (and)
368     probability of good outcome =  $1-NS = 1/2+1/2*Stability = 1-2/\pi O(1)$ .
369
370 (13) In P(Good) RHS:
371 -----
372 If the error probability of voter is 0 and probability of good decision is 1 then binomial summation becomes  $nCn*(p)^n$ 
373
374 (14) In P(Good) LHS:
375 -----
376 If error probability of dictator boolean function is 0 and p=1 then:
377      $p = 1 - \text{NS}(\text{DictatorFunction})$ 
378      $= 1 - \delta^{1.5}$ 
379
380 Similar to RHS  $p=1$  iff  $\delta=0$ 
381 Thus if there is no Noise on either side LHS=RHS (or) LHS is a P algorithm to RHS EXP or PH=DC. This depends on exist

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382
383 (15) [Benjamini-Kalai-Schramm] theorem states the condition for a boolean function to be noise sensitive:
384 A boolean function is noise sensitive if and only if L2 norm (sum of squares) of influences of variables in f tends to
385 Therefore, for stability any voter boolean function in P(Good) RHS should not have the L2 norm of influences to tend
386
387 (16) "How much increasing sets are positively correlated" by [Talagrand] - http://boolean-analysis.blogspot.in/2007/6/Weight\(f\) = sum\_1\_to\_n\(fouriercoeff\(i\)\) <= 0\(mean^2\*1/log\(mean\)\)
388 where Weight of boolean function f in n variables is the sum of squares of n fourier coefficients and mean is Pr(f(x)
389
390 (17) By Majority is Stablest Theorem if P(Good) RHS is a boolean function composition of Maj*Maj=Majn(Maj1,Maj2,...,M
391 (1-2/pi * arccos(rho))*(1-2/pi * arccos(rho)) assuming that stability of the composition is the product like other
392 If the LHS of P(Good) is the Dictator Boolean Function its stability is (rho)^n (because all bits have to be flipped)
393 [cos(pi/2*(1-(rho)^n))]^2 = rho
394
395 For rho=0:
396 -----
397 [cos (pi/2*(1-0^n))]^2 = 0 hence LHS=RHS
398
399 For rho=1:
400 -----
401 [cos (pi/2*(1-1^n))]^2 = 1 hence LHS=RHS
402
403 But for rho=0.5:
404 -----
405 arccos 1/sqrt(2) = pi/2*(1-0.5^n)
406 n = log(1-2/pi*0.7071)/log(0.5)
407 n = 0.863499276 which is quite meaningless probably hinting that for uniform distribution the parity size n is < 1.
408
409 (18) In RHS the P(Good) binomial coefficient summation in terms of Noise Sensitivities of each Voter SAT:
410 nC0(1-NS)^0(NS)^n + nC1(1-NS)^1(NS)^(n-1) + nC2(1-NS)^2(NS)^(n-2) + ...
411 Above summation should ideally converge to holistic Noise Sensitivity of the Boolean Function Composition of Maj*Maj
412 1/2 + 1/2*(1-2/pi*arccos(rho))^2 = nC0(1-NS)^0(NS)^n + nC1(1-NS)^1(NS)^(n-1) + nC2(1-NS)^2(NS)^(n-2) + ...
413
414 If each voter has boolean function with varied Noise Sensitivities, above becomes a Poisson Trial instead of Bernoull
415
416 (19) There are classes of boolean functions based on percolation crossings ( http://arxiv.org/pdf/1102.5761.pdf - Noi
417
418 For epsilon=o(1/n^2*alpha4), Pr[fn(sequence)=fn(sequence with epsilon perturbation)] tends to zero at infinity where
419
420 Open question: If Percolation Boolean Functions are 100% noise stable (as in infinite grid previously), what is the l
421
422 (*IMPORTANT* - this requires lot of reviewing - if correct places a theoretical limit on when stability occurs) From
423
424 (20) Noise stability in terms of Fourier coefficient weights is defined as:
425 summation( rho^k * W^k ) for all degree-k weights where W = summation(fourier_coeff(S)^2) for all |S|, S in [
426
427 (21) Variant 1 of Percolation as a Judge boolean function is defined in 53.4 below which is in non-uniform NC1. If th
428
429 (22) Also from Theorem 5.17 - [RyanO'Donnell] - http://analysisofbooleanfunctions.org/ - for any rho in [0,1], Stabili
430 2/pi*arcsin 0 0 0 Stab00[Majn] 00 2/pi*arcsin 00 + 0(1/(sqrt(1-rho^2)*sqrt(n))).
431
432 (23) Peres' Theorem rephrases above bound for NoiseStability in terms of NoiseSensitivity for class of uniform noise
433 NoiseSensitivity00[f] 00 0(sqrt(00))
434
435 (24) From http://arxiv.org/pdf/1504.03398.pdf: [Boppana-Linial-Mansour-Nisan] theorem states that influence of a bool
436 Inf(f) = 0((logS)^d-1)
437
438 (25) [Benjamini-Kalai-Schramm] Conjecture (different from Majority is least stable BKS conjecture which is still open)
439 Every monotone boolean function f can be epsilon (e) approximated by a circuit of depth d and of size exp((K(e)*Inf(f
440
441 (26) Class of uniform noise stable LTFs in (23) are quite apt for Voter Boolean Functions in the absence of 100% noise
442
443 -----
444 Additional References:
445 -----
446 14.1 k-SAT and 3-SAT - http://cstheory.stackexchange.com/questions/7213/direct-sat-to-3-sat-reduction
447 14.2 k-SAT and 3-SAT - http://www-verimag.imag.fr/~duclos/teaching/inf242/SAT-3SAT-and-other-red.pdf
448 14.3 Switching Lemma
449 14.4 Donald Knuth - Satisfiability textbook chapter - http://www-cs-faculty.stanford.edu/~uno/fasc6a.ps.gz - Quoted e
450 " ... Section 7.2.2.2 Satisfiability
451 Satisfiability is a natural progenitor of every NP-complete problem00
452 Footnote: At the present time very few people believe that P = NP. In other words, almost everybody who has studied
453 14.5 Majority and Parity not in AC0 - www.cs.tau.ac.il/~safran/ACT/CCandSpaceB.ppt, http://www.math.rutgers.edu/~sk12/
454 14.6 Sampling Fourier Polynomials - http://cstheory.stackexchange.com/questions/17431/the-complexity-of-sampling-app
455
456 14.7 Kummer's theorem on binomial coefficient summation - quoted from Wikipedia:
457 "In mathematics, Kummer's theorem on binomial coefficients gives the highest power of a prime number p dividing a binom
458
459 14.8 Summation of first k binomial coefficients for fixed n:
460 - http://mathoverflow.net/questions/17202/sum-of-the-first-k-binomial-coefficients-for-fixed-n
461 - https://books.google.co.in/books?id=Tn0pBAAQBAJ&pg=PA61&lpg=PA61&dq=summation+of+first+k+binomial+coefficients&sc
462

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463 which imply bounds for the summation:
464 - sum_k_2n(2nCi) = 2^2n - sum_0_k-1(2nCi)
465 - 2^2n - sum_0_k-1(2nCi) > 2^2n - (2nCk) * 2^(2n) / 2^(2nCn)
466
467 14.9 Probabilistic boolean formulae - truth table with probabilities - simulates the Voter Circuit SAT with errors
468 http://www.cs.rice.edu/~kvp1/probabilisticboolean.pdf
469
470 14.10 BPAC circuits ( = Probabilistic CNF?)
471 http://www.cs.jhu.edu/~lixints/class/nw.pdf
472
473 14.11 Mark Fey's proof of infinite version of May's theorem for 2 candidate majority voting - Cantor set arguments for
474 https://www.rochester.edu/college/faculty/markfey/papers/MayRevised2.pdf
475
476 14.12 Upperbounds for Binomial Coefficients Summation - http://mathoverflow.net/questions/17202/sum-of-the-first-k-binomial-coefficients
477 f(n,k)= 2^(n-k)*exp((n-2k)^2/4(1+k))
478 for f(n,k) = sum_i_0_to_k(nCi). Proof by Lovasz at: http://yaroslavvb.com/upload/lovasz-proof2.pdf
479
480 -----
481 14.13 (*IMPORTANT*) Connections between Hypergeometric series and Riemann Zeta Function :
482 -----
483 - http://matwbn.icm.edu.pl/ksiazki/aa/aa82/aa8221.pdf - This relation implies that:
484 - P(good) binomial coefficient infinite series summation (and hence the Psuedorandom Vs Majority Voting circuit
485 - and Complement Function circuit special case for RZF (and hence the Euler-Fourier polynomial for Riemann Zeta
486 are deeply intertwined. Kummer theorem gives the p-adic number (power of a prime that divides an integer) for dividir
487
488 Above implies that binomial coefficients can be written in terms of prime powers and vice-versa: P(good) series can be
489
490 -----
491 14.15 ACC circuits and P(Good) RHS circuit
492 -----
493 ACC circuits are AC circuits augmented with mod(m) gates. i.e output 1 iff sum(xi) is divisible by m. It is known that
494
495 -----
496 14.16. Infinite Majority as Erdos Discrepancy Problem
497 -----
498 Related to (132) - May's Theorem proves conditions for infinite majority with sign inversions {+1,-1} and abstention
499
500 14.17 Noise Sensitivity of Boolean Functions and Percolation - http://arxiv.org/pdf/1102.5761.pdf, www.ma.huji.ac.il,
501
502 14.18 Binomial distributions, Bernoulli trials (which is the basis for modelling voter decision making - good or bad
503
504 14.19 Fourier Coefficients of Majority Function - http://www.contrib.andrew.cmu.edu/~ryanod/?p=877, Majority and Complexity
505
506 14.20 Hastad's Switching Lemma - http://windowsontheory.org/2012/07/10/the-switching-lemma/, http://www.contrib.andrew.cmu.edu/~ryanod/?p=547#propdt
507
508 14.21 Degree of Fourier Polynomial and Decision tree depth - http://www.contrib.andrew.cmu.edu/~ryanod/?p=547#propdt
509
510 14.22 Judgement Aggregation (a generalization of majority voting) - Arriving at a consensus on divided judgements - http://www.contrib.andrew.cmu.edu/~ryanod/?p=547#propdt
511
512 14.23 Noise and Influence - [Gil Kalai, ICS2011] - https://gilkalai.files.wordpress.com/2011/01/ics11.ppt
513
514 14.24 Doctrinal Paradox (or) Discursive dilemma - Paradoxes in Majority voting where both Yes and No are possible in
515
516
517 -----
518 15. (FEATURE - DONE-Minimum Implementation using NetworkX algorithms) Add Graph Search (for example subgraph isomorphism)
519
520 16. (FEATURE - DONE) Use of already implemented Bayesian and Decision Tree Classifiers on astronomical data set for p
521
522 17. (FEATURE - DONE) Added Support for datasets other than USGS EQ dataset(parseUSGSdata.py). NOAA HURDAT2 dataset has
523
524 18. (FEATURE - Minimum Functionality DONE-TwitterFollowersGraphRendering, Centrality) (Astro)PsychoSocialAnalysis
525
526 References:
527 -----
528 18.1 Networks,Crowds,Markets - http://www.cs.cornell.edu/home/kleinber/networks-book/networks-book.pdf
529 18.2 Introduction to Social Network Methods - http://faculty.ucr.edu/~hanneman/nettext/
530 18.3 Bonacich Power Centrality - http://www.leonidzhukov.net/hse/2014/socialnetworks/papers/Bonacich-Centrality.pdf
531 18.4 Modelling Human Emotions - http://www.jmlr.org/proceedings/papers/v31/kim13a.pdf
532 18.5 Depression Detection - http://www.ubiwot.cn/download/A%20Depression%20Detection%20Based%20on%20Sentiment
533 18.6 Market Sentiments - http://www.forexfraternity.com/chapter-4-fundamentals/sentiment-analysis/the-psychology-of-sentiment
534 18.7 Sentiment Analysis - http://www.lct-master.org/files/MullenSentimentCourseSlides.pdf
535 18.8 Dream Analysis - http://cogprints.org/5030/1/NRC-48725.pdf
536 18.9 Opinion Mining - http://www.cs.uic.edu/~liub/FBS/SentimentAnalysis-and-OpinionMining.pdf
537 18.10 Linked - [Albert Laszlo Barabazi] - [Ginestra Bianconi - http://www.maths.qmul.ac.uk/~gbianconi/Condensation.html]
538 18.11 Small World Experiment and Six Degrees of Separation - [Stanley Milgram] - https://en.wikipedia.org/wiki/Small-world
539 18.12 LogLog estimation of Degrees in Facebook graph - 3.57 Degrees of Separation - https://research.facebook.com/blc
540
541 19. (FEATURE - DONE-PAC Learnt Boolean Conjunction) Implement prototypical PAC learning of Boolean Functions from data
542 19.1 There are two datasets - dataset1 of size 2^n of consecutive integers and dataset2 of first n-bit prime
543 19.2 Each element of dataset1 is mapped to i-th bit of the corresponding prime number element in the dataset2

```

544 19.3 Above step gives i probabilistic, approximate, correct learnt boolean conjunctions for each bit of all t
 545 19.4 Reference: PAC Learning - <http://www.cis.temple.edu/~giorgio/cis587/readings/pac.html>
 546 19.5 PAC Learnt Boolean Conjunction is an approximated Decision Tree.
 547 19.6 PAC learning is based on Occam's Razor (no unnecessary variables)
 548 PAC Learning implementation for learning patterns in Binary encoded first 10000 Prime Numbers have been committed to
 549
 550 20. (FEATURE - DONE) Integrate AstroInfer to VIRGO-KingCobra-USBmd Platform which makes it an Approximately Intelligent
 551 20.1 Usual cloud platforms support only application-application layer RPCs over an existing operating system.
 552 20.2 NeuronRain differs in that aspect by adding new cloud features (with advanced features in development) like
 553 20.3 Cloud support within kernelspace has lot of advantages - low network latency because of kernelspace-kerne
 554 20.4 Kernelspace-Kernelspace communication is a privileged mode privy to kernel alone and userspace applicati
 555 20.5 At present the data sent over kernel sockets is not encrypted which requires OpenSSL in kernel. Kernel does
 556 20.6 There are ongoing efforts to provide Transport Layer Security (TLS) in kernel sockets which are not yet m
 557 20.6.1 KTLS - [DaveWatson - Facebook] - <https://lwn.net/Articles/666509/> and <https://github.com/ktls/>
 558 20.6.2 IPSec for kernel sockets - [SowminiVaradhan - Oracle] - <http://www.netdevconf.org/1.1/proceedin>
 559 20.7 Usual userspace-userspace network communication has following routing - user1---kernel1---kernel2---us
 560
 561 21. (FEATURE - DONE-Minimum Implementation) Unsupervised Named Entity Recognition and Part-of-Speech tagging using C
 562 #####
 563 A. Design Notes on Mining Numerical Datasets
 564 #####
 565
 566 22. (FEATURE - DONE-Minimum Implementation) Period Three theorem (www.its.caltech.edu/~matilde/LiYorke.pdf) which is
 567
 568 23. (FEATURE - DONE) Entropy of numerical data - Sum of $-\Pr(x)\log\Pr(x)$ for all possible outcome probabilities for a r
 569
 570 #####
 571
 572 ======
 573 574 (THEORY) DECIDABILITY OF EXISTENCE AND CONSTRUCTION OF COMPLEMENT OF A FUNCTION (important draft additions to <http://>
 575 ======
 576
 577 (*24. (DONE) COMPLEMENT OF A FUNCTION - Approximating or Interpolating with a Polynomial: This is quite expensive as
 578 p(t) = 1/N [X0 + X1*e^(2*pi*i*t) + ... upto XN] and
 579 p(n/N) = xn
 580 Thus DFT and interpolation coincide in the above.
 581
 582 -----
 583 24a. Theorems on prime number generating polynomials - special case is to generate all primes or integral complement
 584 -----
 585 Legendre - There is no rational algebraic function which always gives primes.
 586 Goldbach - No polynomial with integer coefficients can give primes for all integer values
 587 Jones-Sato-Wada-Wiens - Polynomial of degree 25 in 26 variables whose values are exactly primes exists
 588
 589 Polynomial interpolation and Fourier expansion of the boolean function in <http://arxiv.org/pdf/1106.4102v1.pdf> probat
 590
 591 -----
 592 24b. Circuit construction for the complement function boolean DNF constructed in <http://arxiv.org/pdf/1106.4102v1.pdf>
 593 -----
 594 The DNF constructed for complement function has to be minimized (through some lowerbound techniques) before it is rep
 595 Old draft of the complement function - https://sites.google.com/site/kuja27/ComplementOfAFunction_earlier_draft.pdf?e
 596
 597 Due to equivalence of Riemann Zeta Function and Euler's theorem - $\text{inverse}(\text{infiniteproduct}(1-1/p(i)^z))$ for all primes
 598 Fourier polynomial of a boolean formula is of the form:
 599 $f(x) = \text{Sigma}_S(\text{fouriercoeff}(S)\text{parityfn}(S))$
 600
 601 and is multilinear with variables for each input. S is the restriction or powerset of the bit positions.
 602
 603 Thus if a prime number is b-bit, there are b fourier polynomials for each bit of the prime. Thus for x-th prime number
 604 $P(x) = 1+2^*fx1(x)+2^2*fx2(x)....+2^b*fxb(x)$
 605 where each $fxi()$ is one of the b fourier expansion polynomials for prime bits.
 606
 607 -----
 608 24c. Riemann Zeta Function written as Euler-Fourier Polynomial :
 609 -----
 610 Fourier polynomials for each prime can be substituted in Euler formula and equated to Riemann Zeta Function:
 611 $RZF = \text{Inverse}((1-1/P(x1)^s)(1-1/P(x2)^s))...ad infinitum$
 612
 613 Non-trivial complex zero s is obtained by,
 614 $P(xi)^s = 1$
 615 $P(xi) = (1)^{1/s}$
 616 $1+2^*fx1(xi)+2^2*fx2(xi)....+2^b*fxb(xi) = (1)^{(e^{(-i*\theta)})/r}$ after rewriting in phasor notation $s=r*e^{(i*\theta)}$
 617
 618 Above links Fourier polynomials for each prime to roots of unity involving non-trivial zeroes of Riemann Zeta Function
 619 LHS is multilinear with at most b variables for b bits of the prime number. A striking aspect of the above is that Fc
 620
 621
 622
 623
 624

706
707 (5) can also be written as,
708
709 $\ln P(x_i)^k = \ln(\sec(l * \ln(P(x_i))))$
710
711 $k = \ln[\sec(l * \ln(P(x_i)))] / \ln P(x_i)$ ----- (1)
712
713 By RH k has to be 0.5 irrespective of RHS.
714
715 Approximation of l:
716
717 By assuming k=0.5 and Using series expansion of $\cos(x)$ - choosing only first two terms, l is approximately,
718
719 $P(x_i) = 1/[\cos(l * \ln(P(x_i)))]^2$ ----- (1)
720
721 $l = \sqrt{2} * \sqrt{\sqrt{P(x_i)} - 1} / \ln(P(x_i))$ ----- (1)
722
723 More on (7):
724
725 $\tan(l * \ln(P(x_i))) = 0$ implies that $l * \ln(P(x_i)) = n * \pi$ for some integer n.
726
727 $\ln(P(x_i)) = n * \pi / l$
728
729 $P(x_i) = e^{(n * \pi / l)}$ ----- (1)
730
731 Above equates the Fourier polynomial for xi-th prime in terms of exponent l of some RZF zero
732
733 24g. Ramanujan Graphs, Ihara Zeta Function and Riemann Zeta Function and Special case of Complement Function
734
735 A graph is Ramanujan graph if it is d-regular and eigen values of its adjacency matrix are $\sqrt{d-1} * 2$ or d. Ihara ze
736
737 If a set of p-regular graphs for all primes is considered, then Riemann Zeta Function can be derived (using Ihara Zeta
738
739 [If an eigen value is t ($\leq q$), then it can be derived that
740 $q^s = q + (\text{or}) - \sqrt{q^2 - 4t} / 2$
741 where $s=a+ib$. Setting $a=0.5$ is creating a contradiction apparently which is above divided by \sqrt{q} (while equating
742
743 Above and the Informal notes in <https://sites.google.com/site/kuja27/RamanujanGraphsRiemannZetaFunctionAndIharaZetaFunction>
744
745 Disclaimer: It is not in anyway an attempted proof or disproof of RH as I am not an expert in analytical number theor
746
747 (1) For some i-th prime+1 regular graph (i.e $q+1$ regular graph where q_i is prime),
748
749
$$\frac{[1+q_i^{-s}]}{[z_i(s) \det(I - A * q_i^{-s}) + q_i^{-(1-2s)} * I]^{1/|V|-|E|}} = \frac{1}{[1-q_i^{-s}]}$$

750
751
752 (2) Infinite product of the above terms for all prime+1 regular graphs gives the RZF in right in terms of
753 Ihara Zeta Function Identities product on the left - The infinite set of prime+1 regular graphs relate to
754 RZF zeros.
755
756 (3) For non-trivial zeros $s=a+ib$, RZF in RHS is zero and thus either numerator product is zero or denominator product
757
758 (4) From Handshake Lemma, it can be derived that a q-regular graph with order n ($=|V|$ vertices) has
759 $q^n/2$ edges ($=|E|$ edges)
760
761 (5) If numerator is set to zero in LHS,
762 $q^{(a+ib)} = -1$
763 and
764 $\cos(b \log q) + i \sin(b \log q) = -1/q^a$ which seems to give further contradiction
765
766 (6) If denominator is set to infinity in LHS,
767 $[z_1 * z_2 * \dots * \det() * \det() * \dots]^{1/|V|-|E|} = \text{Inf}$
768
769 (or)
770 $[z_1 * z_2 * \dots * \det() * \det() * \dots]^{1/|E|-|V|} = 0$
771
772 for some term in the infinite product of LHS which implies that
773 $[z_1 * z_2 * \dots * \det() * \det() * \dots] = 0$ which is described earlier above in the notes.
774
775 (7) More derivations of the above are in the notes uploaded in handwritten preliminary drafts at:
776 (7.1) https://sites.google.com/site/kuja27/RZFAndIZF_25October2014.pdf?attredirects=0&d=1
777 (7.2) http://sourceforge.net/p/asfer/code/HEAD/tree/python-src/ComplFunction_DHF_PVsNP_Misc_Notes.pdf
778
779 (8) By equating the determinant in (6) above to zero, written notes in (7) derive values of $s=a+ib$ for non-Ramanujan
780
781 (9) Above doesn't look circular also because infinite product of characteristic polynomials - determinants - are inde
782
783 (10) Expression in (1) for a prime+1 regular graph can also be equated to Euler-Fourier polynomial mentioned in (24c)
784
785
$$\frac{[1+q_i^{-s}]}{[z_i(s) \det(I - A * q_i^{-s}) + q_i^{-(1-2s)} * I]^{1/|V|-|E|}} = \frac{1}{[1 - P(x_i)^{-s}]}$$

```

787 (11)  $q_i$  can be replaced with Fourier polynomial  $P(x_i)$ , and the above becomes:
788  $[1-P(x_i)^{-2s}] = [z_i(s)\det(I-A^*P(x_i)^{-s} + P(x_i)^{(1-2s)*I}]^{(1/|V|-|E|)}$ 
789 (or)  $[1-P(x_i)^{-2s}]^{(|V|-|E|)} = [z_i(s)\det(I-A^*P(x_i)^{-s} + P(x_i)^{(1-2s)*I}]$ 
790
791 (12) LHS of (11) can be expanded with binomial series. Thus Euler-Fourier polynomial is coalesced into Ihara identity
792
793 (13) ACC circuits have support for  $\text{mod}(m)$  gates. Thus a trivial circuit for non-primality is set of  $\text{mod}(i)$  circuits -
794
795 (14) The Fourier polynomial of a prime  $P(x_i)$  is holographic in the sense that it has information of all primes due to
796
797 (15) Without any assumption on Ihara and Riemann Zeta Functions, for any  $(q+1)$ -regular graph for prime  $q$ , just solving
798
799 (16) In (15), even the fact that  $q$  has to be prime is redundant. Just solving for  $q^s + q^{(1-s)} = \text{some\_eigen\_value } q$ 
800
801 (17) Assuming  $\text{Real}(s)=0.5$  from 7.1 and 7.2, it can be derived with a little more steps that  $\text{eigen\_value} = 2*\sqrt{q}*\epsilon$ 
802
803 (18) It is not known if  $\{\text{Imaginary}(RZF\_zero)\} = \{\text{Imaginary}(s)\}$ . If not equal this presents a totally different problem
804
805 (19) Maximum eigen value of  $(q+1)$ -regular graph is  $(q+1)$  and the infinite set  $\{\text{Imaginary}(s)\}$  can be derived from eigenvalues
806
807 (20) An experimental python function to iterate through all  $\{\text{Imaginary}(s)\}$  mentioned in (19) supra has been included
808
809 (21) (SOME EXPERIMENTATION ON DISTRIBUTION OF PRIMES) List of primes read by complement.py is downloaded from https://sourceforge.net/p/asfer/code/HEAD/tree/python-src/
810
811 -----
812 24h. PAC Learning and Complement Function Construction
813 -----
814 Complement Boolean Function construction described in http://arxiv.org/abs/1106.4102 is in a way an example of PAC learning
815 - There are two datasets - dataset1 of size  $2^n$  of consecutive integers and dataset2 of first  $n$ -bit prime numbers
816 - Each element of dataset1 is mapped to  $i$ -th bit of the corresponding prime number element in the dataset2. E.g.
817 - Above step gives  $n$  probabilistic, approximate, correct learnt boolean conjunctions for each bit of all the
818 - An example PAC Boolean Conjunction Learner is at: http://sourceforge.net/p/asfer/code/HEAD/tree/python-src/
819
820 -----
821 24i. Star Complexity and Complement Function Circuit Lowerbound (related to 198)
822 -----
823 Star Complexity of a Boolean Circuit is the minimum number of AND and OR gates required in monotone circuit graph. Similar
824
825 -----
826 24j. Additional references:
827 -----
828 24.1 Google groups thread reference 2003 (OP done by self): https://groups.google.com/forum/#!search/ka\_shrinivaasan
829 24.2 Math StackExchange thread 2013: http://math.stackexchange.com/questions/293383/complement-of-a-function-f-2n-n-1
830 24.3 Theory of Negation - http://mentalmodes.princeton.edu/skhemlani/portfolio/negation-theory/ and a quoted excerpt
831 "... The principle of negative meaning: negation is a function that takes a single argument, which is a set of fully
832 24.4 Boolean Complementation [0 or 1 as range and domain] is a special case of Complement Function above (DeMorgan th)
833 24.5 Interpolation - http://caig.cs.nctu.edu.tw/course/NM07S/slides/chap3\_1.pdf
834 24.6 Formal Concept Analysis - http://en.wikipedia.org/wiki/Formal\_concept\_analysis, http://ijcai.org/papers11/Papers
835 24.7 Prime generating polynomials - http://en.wikipedia.org/wiki/Formula\_for\_primes
836 24.8 Patterns in primes - every even number  $> 2$  is sum of 2 primes - Goldbach conjecture : http://en.wikipedia.org/wiki/Goldbach\_conjecture
837 24.9 Arbitrarily Long Arithmetic progressions - Green-Tao theorem: http://en.wikipedia.org/wiki/Green%2680%93Tao\_theorem
838 24.10 Prime generating functions - https://www.sonomia.edu/math/colloq/primes\_sonomia\_state\_9\_24\_08.pdf
839 24.11 Hardness of Minimizing and Learning DNF Expressions - https://cs.nyu.edu/~khot/papers/minDNF.pdf
840 24.12 DNF Minimization - http://users.cms.caltech.edu/~umans/papers/BU07.pdf
841 24.13 DNF Minimization - http://www.cs.toronto.edu/~toni/Papers/mindnf.pdf
842 24.14 Riemann Zeta Function Hypothesis - all non-trivial(complex) zeroes of RZF have  $\text{Re}(z) = 0.5$  - http://en.wikipedia.org/wiki/Riemann\_zeta\_function
843 24.15 Frequent Subgraph Mining - http://research.microsoft.com/pubs/173864/icde08gsearch.pdf
844 24.16 Frequent Subgraph Mining - http://glaros.dtc.umn.edu/gkhome/fetch/papers/sigmod05.pdf
845 24.17 Roots of polynomials - Beauty of Roots - http://www.math.ucr.edu/home/baez/roots/
846 24.18 Circuit lowerbounds (Gate Elimination, Nechiporuk, Krapchenko, etc) - http://cs.brown.edu/~jes/book/pdfs/Models.pdf
847 24.19 Schwartz-Zippel Lemma for Polynomial Identity Testing - http://en.wikipedia.org/wiki/Schwartz%2680%93Zippel\_lemma
848 24.20 Schwartz-Zippel Lemma for PIT of multilinear polynomials - http://www.cs.huji.ac.il/~noam/degree.ps
849 24.21 Analysis of Boolean Functions - http://analysisofbooleanfunctions.org/
850 24.22 Riemann-Siegel Formula for computation of zeros - http://numbers.computation.free.fr/Constants/Miscellaneous/zeta.html
851 24.23 RZF zeros computation - http://math.stackexchange.com/questions/134362/calculating-the-zeroes-of-the-riemann-zeta-function
852 24.24 Online Encyclopedia of Integer Sequences for Prime numbers - all theorems and articles related to primes - http://www.oeis.org
853 24.25 Intuitive proof of Schwartz-Zippel lemma - http://rjlipton.wordpress.com/2009/11/30/the-curious-history-of-the-schwartz-zippel-lemma/
854 24.26 Random Matrices and RZF zeros - http://www.maths.bris.ac.uk/~majpk/papers/67.pdf
855 24.27 Circuit for determinant - S. J. Berkowitz. On computing the determinant in small parallel time using a small number of additions
856 24.28 Mangoldt Function, Ihara Zeta Function, Ramanujan Graphs - http://lucatrevisan.wordpress.com/2014/08/18/the-riemann-zeta-function-and-prime-numbers/
857 24.29 Multiplicity of an eigen value in  $k$ -regular graph - http://math.stackexchange.com/questions/255334/the-number-of-eigenvalues-of-a-k-regular-graph
858 24.30 PAC Learning - http://www.cis.temple.edu/~giorgio/cis587/readings/pac.html
859 24.31 Pattern in Prime Digits - [Oliver-Kannan Soundararajan] - https://arxiv.org/abs/1603.03720 - Prime numbers which
860 24.32 Pattern in Prime Digits - http://www.nature.com/news/peculiar-pattern-found-in-random-prime-numbers-1.19550 - e.g.
861 24.33 Pattern in Primes - Ulam's Spiral - [Stanislaw Ulam] - https://www.alpertron.com.ar/ULAM.HTM - Prime numbers as
862 24.34 Theory of Negation (Broken URL in 24.3 updated) - http://mentalmodes.princeton.edu/papers/2012negation.pdf
863 24.35 Prime Number Theorem -  $n$ -th prime is  $\sim O(n\log n)$ 
864 24.36 Riemann Hypothesis prediction of prime distribution -  $\text{Integral}_2 p(n)_{[dt/\log t]} = n + O(\sqrt{n(\log n)^3})$ 
865 24.37 Brainfuck Turing Machine Compiler - https://esolangs.org/wiki/Brainfuck
866 24.38 Laconic Turing Machine Compiler - https://esolangs.org/wiki/Laconic
867 24.39 Circuit Complexity Lowerbound for Explicit Boolean Functions - http://logic.pdmi.ras.ru/~kulikov/papers/2011\_3r.pdf

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868 24.40 Star Complexity of Boolean Function Circuit - [Stasys Jukna] - http://www.thi.informatik.uni-frankfurt.de/~jukr
869 24.41 Random Matrices, RZF zeroes and Quantum Mechanics - https://www.ias.edu/ideas/2013/primes-random-matrices
870 24.42 Jones-Sato-Wada-Wiens Theorem - Polynomial of 25 degree-26 variables for Prime Diophantine set - http://www.mathpages.com/home/kmath26.htm
871 24.43 Energy levels of Erbium Nuclei and zeros of Riemann Zeta Function - http://seedmagazine.com/content/article/prime-energy-levels-erbium-nuclei-and-zeros-riemann-zeta-function
872 #####
873 #####
874 #####
875 25. (FEATURE - DONE) Approximating with some probability distribution - Gaussian, Binomial etc., that model the proba
876 (FEATURE - DONE) 26. Streaming algorithms - Finding Frequency moments, Heavy Hitters(most prominent items), Distinct
877 (FEATURE - DONE) 26.1 Implementation of LogLog and HyperLogLog Counter(cardinality - distinct elements in streamed mu
878 (FEATURE - DONE) 26.2 Parser and non-text file Storage framework for Realtime Streaming Data - Hive, HBase, Cassandra
879 (FEATURE - DONE) 26.3 Python scripts for Stock Quotes Data and Twitter tweets stream search data for a query.
880 -----
881 References:
882 -----
883 26.4 https://gist.github.com/debasishg/8172796
884 -----
885 27. (FEATURE - DONE) Usual Probabilistic Measures of Mean, Median, Curve fitting on the numeric data. Python+RPy2+R i
886 28. (FEATURE - DONE - using python, R+rpy2) Application of Discrete Fourier Transform(using R), LOESS(using R), Linea
887 29. (FEATURE - DONE) Least Squares Method on datapoints y(i)s for some x(i)s such that f(x)~y needs to be found. Comp
888 (FEATURE - DONE) 30. K-Means and kNN Clustering(if necessary and some training data is available) - unsupervised and s
889 31. (FEATURE - DONE) Discrete Hyperbolic Factorization - Author has been working on a factorization algorithm with el
890 32. (FEATURE - DONE) Multiple versions of Discrete Hyperbolic Factorization algorithms have been uploaded as drafts i
891 32.1) http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicFactorization\_UpperboundDerivedWithLogLogLog
892 32.2) http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM
893 33. (DONE) NC PRAM version of Discrete Hyperbolic Factorization:
894 33.1) An updated NC PRAM version of Discrete Hyperbolic Factorization has been uploaded at:
895 http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM
896 33.2) Preliminary Design notes for CRCW PRAM implementation of the above is added to repository at: http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM
897 34. (FEATURE - DONE) An updated draft version of PRAM NC algorithm for Discrete Hyperbolic Factorization has been upl
898 34.1 LaTeX - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM.tex
899 34.2 PDF - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM.pdf
900 -----
901 Additional references:
902 -----
903 34.3) Above PRAM k-merge algorithm implies Factorization is in NC, a far more audacious claim than Factorizat
904 34.4) (IMPORTANT OPTIMIZATION OVER 34.1, 34.2 ABOVE) Instead of [BerkmanSchieberVishkin] an O(logloglogN) alg
905 34.5) Randomized Algorithms ,Rajeev Motwani and Prabhakar Raghavan, Chapter 12 on Distributed and Parallel Al
906 put size and randomized algorithms for Parallel sort - Definition 12.1 of NC (Page 336) - "NC consists of languages t
907 he O(logN) time and O(N^k) PRAM processors".
908 34.6) Also an alternative merge algorithm in constant depth polysize circuit described in Chandra-Stockmeyer-
909 34.7) [RichardKarp-VijayaRamachandran] define the inclusion of PRAM models in NC in page 29 of http://digitalcommons.acm.org/citation.cfm?doid=128.128.128.128
910 34.8) Parallel RAM survey - http://www.cs.utoronto.ca/~faith/PRAMsurvey.ps
911 34.9) Related: Quantum Search using Grover Algorithm over unsorted lists can be done in O(sqrt(N)) - https://www.academy.com/10.1145/1060365.1060366
912 34.10) Recent Advances in All Nearest Smaller Values algorithms:
913 34.10.1) ANSV in hypercube - Kravets and Plaxton - http://www.cs.utexas.edu/~plaxton/pubs/1996/ieee\_t
914 34.10.2) ANSV lowerbound - Katajainen - http://www.diku.dk/~jyrki/Paper/CATS96.ps - omega(n) processc
915 34.10.3) ANSV in BSP machines - Chun Hsi Huang - http://www.cse.buffalo.edu/tech-reports/2001-06.ps
916 34.11) The crucial fact in the above is not the practicality of having order of n parallel processors with RA
917 34.12) Rsync - PhD thesis - chapters on external and internal sorting - https://www.samba.org/~tridge/phd\_thesis.pdf
918 34.13) Handbook of Parallel Computing - [SanguthevarRajasekaran-JohnReif] - http://www.engr.uconn.edu/~rajasekaran/HPC.pdf
919 34.14) [Eric Allender] - NC^1 and EREW PRAM - March 1990 - https://groups.google.com/forum/#!topic/comp.theory/NC1-EREW-PRAM
920 34.15) Efficient and Highly Parallel Computation - [JeffreyFinkelstein] - https://cs-people.bu.edu/jeffreyfinkelstein/EfficientAndHighlyParallelComputation.pdf
921 34.16) There is a commercially available Parallel CRCW RAM chip implementation by NVIDIA CUDA GPUs - http://www.nvidia.com/cuda/cuda-parallel-crcw-ram

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949 34.17) StackExchange thread on Consequences of Factorization in P - http://cstheory.stackexchange.com/questions/34.17
950 34.18) What happened to PRAM - http://blog.computationalcomplexity.org/2005/04/what-happened-to-pram.html - (Page 29 - HooverGreenlawRuzzo)
951 34.19) [Page 29 - HooverGreenlawRuzzo] - "... but there is no a priori upper bound on the fanout of a gate. + (Page 29 - HooverGreenlawRuzzo)
952 34.20) (DONE-BITONIC SORT IMPLEMENTATION) In the absence of PRAM implementation, NC Bitonic Sort has been implemented
953 34.21) An important point to note in above is that an exhaustive search in parallel would always find a fact
954 34.22) NC Computational Geometric algorithms - [AggarwalChazelleGuibasDunlaingYap] - https://www.cs.princeton.edu/~chazelle/papers/nc.pdf
955 34.23) Parallel Computational Geometry Techniques - [MikhailAtallah] - http://docs.lib.psu.edu/cgi/viewcontent.cgi?article=1000&context=psu\_mathematics
956 34.24) [DexterKozen-CheeYap] - Cell Decomposition is in NC - http://anotherexample.net/order/field53539cff07d3e
957 34.25) Cell decomposition for tessellation of hyperbola can be created in two ways. In the first example, set of integer y-axis lines and hyperbolas
958 34.26) In another example Cell decomposition is created by intersection of integer y-axis lines and hyperbolas
959 34.27) NVIDIA CUDA Parallel Bitonic Sort Implementation Reference - http://developer.download.nvidia.com/compressors/parallel-bitonic.pdf
960 34.28) Tiling of Hyperbolic curve: The discretization step of a hyperbola to form set of contiguous tiled segments
961 34.29) The tiling of hyperbolic curve is done by  $\Delta x = N / [y^{0.001}(y+1)]$  which is a process similar to low-pass filtering
962 34.30) Above algorithm ignores Communication Complexity across PRAMs or Comparator nodes on a Cloud.
963 34.31) Comparison of Parallel Sorting Algorithms (Bitonic, Parallel QuickSort on NVIDIA CUDA GPU etc.,) - http://www.cs.princeton.edu/~chazelle/papers/parallel.pdf
964 34.32) NC-PRAM Equivalence and Parallel Algorithms - [David Eppstein] - https://www.ics.uci.edu/~eppstein/putnam/2000/nc-pram.pdf
965 34.33) Parallel Merge Sort - [Richard Cole - https://www.cs.nyu.edu/~cole/] - best known theoretical parallel algorithm
966 34.34) NC-PRAM equivalence - http://courses.csail.mit.edu/6.854/06/notes/n32-parallel.pdf
967 34.35) Theorem 13 - PRAM( $\text{polylog}, \log$ ) = uniform-NC - www.wisdom.weizmann.ac.il/~oded/PS/CC/l27.ps - This means that PRAM( $\text{polylog}, \log$ ) = uniform-NC
968 34.36) PRAM Implementation Techniques - http://www.doc.ic.ac.uk/~nd/surprise\_95/journal/vol4/fcw/report.html
969 34.37) Logarithm Time Cost Parallel Sorting - [Lasse Natvig] - Survey on Batcher's Bitonic Sort, AKS Sorting
970 34.38) What is wrong with PRAM - "Too much importance is placed on NC . In particular, algorithms which have been implemented in parallel are not necessarily in NC"
971 34.39) NC-PRAM equivalence - https://www.ida.liu.se/~chrke55/courses/APP/ps/f2pram-2x2.pdf - "set of problems for which NC-PRAM is not equivalent to uniform-NC"
972 34.40) Number of PRAMs in NC definition - http://cs.stackexchange.com/questions/39721/given-a-pram-may-use-a-pram
973 34.41) EURO-PAR 1995 - Input size in Parallel RAM algorithms - https://books.google.co.in/books?id=pVpj0wUHE1
974 34.42) Batcher's Bitonic Sort is in NC - https://web.cs.dal.ca/~arc/teaching/CS4125/Lectures/03b-ParallelAnalysis.pdf
975 34.43) Brief Overview of Parallel Algorithms, Work-Time Efficiency and NC - [Blelloch] - http://www.cs.cmu.edu/~blelloch/parallel.pdf
976 34.44) Sorting  $n$  integers is in NC - [BussCookGuptaRamachandran] - www.math.ucsd.edu/~sbuss/ResearchWeb/BooleanAlgebra/BooleanAlgebra.pdf
977 34.45) PRAM and Circuit Equivalence - [Savage] - http://cs.brown.edu/~jes/book/pdfs/ModelsOfComputation.pdf - http://www.cs.cmu.edu/~blelloch/parallel.pdf
978 34.46) Efficient Parallel Computation = NC - [AroraBarak] - http://theory.cs.princeton.edu/complexity/book.pdf
979 34.47) Parallel sorting and NC - http://courses.csail.mit.edu/6.854/06/notes/n32-parallel.pdf
980 34.48) Parallel sorting in PRAM model - http://www.math.ias.edu/~avi/PUBLICATIONS/MYPAPERS/MW87/MW87.pdf
981 34.49) Parallel Sorting is in NC - http://www.toves.org/books/distalg/distalg.pdf - Section 5 (Page 17)
982 34.50) Parallel K-Merge Algorithm for merging  $k$  sorted tiles into a single sorted list - LazyMerge - www.cs.rutgers.edu/~mihai/pubs/lazymerge.pdf
983 34.51) Timsort and its parallel implementation in Java, Python and Android for parallel merge sort of arrays
984 34.52) Comparison of Parallel and Sequential Sorts - https://github.com/darkobozidar/sequential-vs-parallel-sorting
985 34.53) Trigonometric Functions over Finite Galois Fields (of prime power order) - https://arxiv.org/pdf/1501.02180v1.pdf
986 34.54) Adaptive Bitonic Sorting - http://pubs.siam.org/doi/abs/10.1137/0218014 - very old paper (1989) on PRAM
987 34.55) Efficient Parallel Sorting - improvement of Cole's Parallel Sort and AKS sorting networks: sorting networks
988 34.56) Computational Pixelation Geometry Theorems - https://arxiv.org/pdf/1105.2831v1.pdf - defines planar pixelation
989 34.57) Approximating a function graph by planar pixelation - http://www3.nd.edu/~lnicolae/Pixelations-beam.pdf

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1031    34.58) Resource Oblivious Sorting on Multicores - [RichardCole-VijayaRamachandran] - https://arxiv.org/pdf/15
1032    34.59) NC and various categories of PRAMs - https://pdfs.semanticscholar.org/5354/99cf0c2faaaa6df69529605c87
1033    34.60) PRAM-NC equivalence, definition of input size - ftp://ftp.cs.utexas.edu/pub/techreports/tr85-17.pdf -
1034    34.61) PRAM model and precise definition of input size in PRAM models - https://www.cs.fsu.edu/~engelen/courses
1035    34.62) Simulation of Parallel RAMs by Circuits - http://www.cstheory.com/stockmeyer@sbcglobal.net/sv.pdf
1036    34.63) PRAM Models and input size - [Joseph JaJa] - https://www.cs.utah.edu/~hari/teaching/bigdata/book92-JaJa
1037    34.64) Input Size for PRAMs, NC-PRAM equivalence, Cook-Pippenger Thesis, Brent's Speedup Lemma - www.csl.mtu.edu/~amato/pubs/thesis.pdf
1038    34.65) Pixelation of Polygons - On Guarding Orthogonal Polygons with Bounded Treewidth - [Therese Biedl and S
1039    34.66) A Comparison of Parallel Sorting Algorithms on Different Architectures- [NANCY M. AMATO, RAVISHANKAR I
1040    34.67) Bitonic Sort Implementation - [Amrutha Mullapudi] - https://www.cse.buffalo.edu//faculty/miller/Course
1041    34.68) PRAMs and Multicore architectures - http://blog.computationalcomplexity.org/2008/04/revenge-of-parallel
1042    34.69) NC and PRAMs - http://www.cse.iitd.ernet.in/~subodh/courses/CSL860/slides/3pram.pdf
1043    34.70) Geometric Searching, Ray Shooting Queries - [Michael T.Goodrich] - http://www.ics.uci.edu/~goodrich/pu
1044    34.71) Planar Point Location in Parallel - ftp://ftp.cs.brown.edu/pub/techreports/89/cs89-45a.pdf - Section 4
1045    34.72) One dimensional Point Location - https://www.csun.edu/~ctoth/Handbook/chap38.pdf - Section 38.1 - List
1046    34.73) Hoover-Klawe-Pippenger Algorithm for converting arbitrary circuit to bounded fanout 2 - [Ogihara-Anime
1047    34.74) PRAM definition of NC - [Kristoffer Arnsfelt Hansen] - https://users-cs.au.dk/arnsfelt/CT08/scribenote
1048    34.75) Factorization, Planar Point Location in parallel, Cascading, Polygon pixelation of hyperbola - [Mikhail
1049    34.76) Multicores,PRAMs,BSP and NC - [Vijaya Ramachandran] - https://womenintheory.files.wordpress.com/2012/0
1050    34.77) Word Size in a PRAM - https://hal.inria.fr/inria-00072448/document - Equation 5 -  $\log N \leq w$  (N is input)
1051    34.78) Prefix Sum Computation and Parallel Integer Sorting - [Sanguthevar Rajasekaran, Sandeep Sen] - http://www.cs.iitd.ernet.in/~subodh/courses/CSL860/slides/3pram.pdf
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35. (THEORY) Above Discrete Hyperbolic Factorization can be used as a numerical dataset analysis technique. Discrete
#####
B. EXPERIMENTAL NON-STATISTICAL INFERENCE MODEL BASED ON ALREADY KNOWN THEORETICAL COMPUTER SCIENCE RESULTS:
#####
36.1. (FEATURE - DONE-WordNet Visualizer implementation for point 15) The classification using Interview Algorithm De
36.2. (THEORY) Thus if number of classes and documents are infinite, an infinite hypergraph is obtained. This is also
37. (FEATURE - PoC WordNet Visualizer Closure DONE) Above multiplanar hypergraph is quite related as a theoretical cor
38. (THEORY) But above is not context free because context is easily obtainable from the hyperedge which connects mult
39. (THEORY) An interesting academic question to pose is - "Does the above hypergraph have a strong connectivity and a
40. (THEORY) A recent result of Rubik's cube (http://www.cube20.org/) permutations to get solution having a constant c
41. (THEORY) Mapping Rubik's Cube to Concept Wide Hypergraph above - Each configuration in Rubik's Cube transition fur
42. (THEORY) The Multiplanar Primordial Field Turing Machine model described by the author in "Theory of Shell Turing
43. (THEORY) Instead of a wordnet if a relationship amongst logical statements (First Order Logic etc.,) by logical im
44. (THEORY) Implication graphs of logical statements can be modelled as a Random Growth Network where a graph is rar
45. (THEORY) If a statistical constraint on the degree of this graph is needed, power law distributions (Zipf, Pareto
46. (THEORY) Set cover or Hitting Set of Hypergraph is a Transversal of hypergraph which is a subset of set of vertices
47. (THEORY) Random walk on the above concept hypergraph, Cover time etc., which is a markov process. Probably, Cover
48. (THEORY - IMPLEMENTATION - DONE) Tree decomposition or Junction Trees of concept hypergraph with bounded tree wid
49. (THEORY) 2(or more)-dimensional random walk model for thinking process and reasoning (Soccer model in 2-dimension
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As an experimental extension of point 47 for human reasoning process, random walk on non-planar Concept hypergraph (
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1111#####
1112#####
1113 C. Slightly Philosophical - Inferences from conflicting opinions:
1114#####
1115
1116 50. (DONE) As an example, if there are "likes" and "dislikes" on an entity which could be anything under universe - h
1117
1118 51. (DONE) Another philosophical question is what happens to the majority voting when every voter or witness is wrong
1119
1120 52. (THEORY) There is a realword example of the above - An entity having critical acclaim does not have majority accl
1121
1122 53. (THEORY) Items 50,51,52 present the inherent difficulty of perfect judgement or perfect inference. On a related r
1123
1124 -----
1125 53.1 (THEORY) Judge Boolean Function (there doesn't seem to be an equivalent to this in literature - hence it is defi
1126
1127 A Judge Boolean function  $f:(0,1)^n \rightarrow (0,1)$  has two classes of input sets of bit sets  $(x_1, x_2, x_3, \dots)$  and  $(y_1, y_2, y_3, \dots)$ 
1128 - LHS PRG/Dictator boolean function choice can also be thought of as randomly chosen Judge boolean function (
1129 - In RHS, each voter has a judge boolean function above and NoiseStability of Boolean Function Composition of
1130 - An example: From https://sites.google.com/site/kuja27/InterviewAlgorithmInPSPACE.pdf?attredirects=0, Judge
1131 - QBF is PSPACE-complete and hence Judge Boolean Function is PSPACE-complete.
1132 - Thus LHS of P(good) is in PSPACE (a pseudorandomly chosen Judge Boolean Function) while RHS of P(good) is s
1133 - Since Judgement or Choice among two adversaries is a non-trivial problem, it is better to have each Voter's
1134 - Reference: QBF-SAT solvers and connections to Circuit Lower Bounds - [RahulSanthanam-RyanWilliams] - http://
1135 - A complex Judging scenario: Doctrinal Paradox (or) Discursive dilemma - Paradoxes in Majority voting where
1136
1137 -----
1138 53.2 (THEORY) P(Good) Convergence, Voter TQBF function, PH-completeness and EXP-completeness - Adversarial reduction
1139
1140 P(Good) RHS is in PH if depth restricted and in EXP if depth unrestricted. LHS is a pseudorandomly chosen Judge Boolean
1141 Each Voter can be thought of as simulator of both adversaries in Chess i.e Voter TQBF has two sets of inputs  $x_1, x_2, x_3$ 
1142
1143 A special case of Complexity of Quantified 3-CNF Boolean Forumlas is analyzed in http://eccc.hpi-web.de/report/2012/
1144
1145 Depth Hierarchy Theorem , a recent result in 2015 in http://arxiv.org/pdf/1504.03398.pdf proved PH to be infinite rela
1146
1147 -----
1148 53.3 (THEORY- *IMPORTANT* ) Conditions for complexity classes of LHS and RHS of P(Good) summation being equated
1149
1150 RHS of P(Good) is either PH-complete or EXP-complete as mentioned in 53.2.
1151 LHS of P(Good) is a pseudorandomly chosen Judge Boolean Function while RHS is a huge mixture of judge boolean functio
1152
1153 Probability of LHS Judge Boolean Function belonging to a complexity class C with NoiseStability p is =
1154 Probability of LHS PRG choice Judge Boolean Function in complexity class C * Probability of Goodness in terms of Nois
1155 c/n * p where c is the number of judge boolean functions in complexity class C and n is the total number of judge bo
1156
1157 When p=1 and c=n LHS is 1 and is a complexity class C algorithm to RHS PH-complete or EXP-complete DC circuit when R
1158 - boolean function composition in RHS is in some fixed circuit complexity class (PH-complete or EXP-complete) and c
1159 - LHS has to have 100% noise stability
1160 - RHS has to have 100% noise stability
1161 Thus above conditions are to be satisfied for equating complexity classes in LHS and RHS to get a lowerbound result.
1162
1163 If LHS and RHS of P(Good) are not equatable, probability of goodness of LHS and RHS can vary independently and have a
1164 cardinality(RHS) + cardinality(LHS) = cardinality(Universal set of judge boolean functions) (or)
1165 cardinality(RHS) + 1 = cardinality(Universal set)
1166 which is the proverbial "one and all".
1167
1168 Assuming there exists a boolean percolation function with noise stability 100%, voter with such a boolean function cc
1169
1170 -----
1171 53.4 (THEORY) Variant 1 of Percolation as a Judge boolean function (related to 14 above)
1172
1173 Percolation boolean function returns 1 if there is a left-right crossing event in a path within the  $Z^2$  grid random g
1174 There are n parameters on which the voter or a judge weighs two adversaries a and b (each take the 2 coordinates in t
1175
1176 -----
1177 53.5 (THEORY) Variant 2 of Percolation as a Judge boolean function (related to 14 above)
1178
1179 53.5.1 Both x and y axes have the criteria common to both adversaries a and b as coordinates.
1180 53.5.2 If adversary a is equal to b for a criterion c, then there is a horizontal left-right edge with probability p.
1181 53.5.3 If adversary b is better than a for criterion c, then there is a vertical edge (down-top) with probability p.
1182 53.5.4 If adversary a is better than b for criterion c, then there is a vertical edge (top-down) with probability p.
1183
1184 53.5.5 Example 1:
1185
1186 criterion a b
1187 c1 5 4 (top-down)
1188 c2 3 5 (down-top)
1189 c3 2 2 (left-right)
1190 c4 4 6 (down-top)
1191 c5 7 8 (down-top)

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1192
1193      21  25  (a < b)
1194
1195
1196 53.5.6 Example 2:
1197
1198 criterion   a   b
1199 c1          2   1 (top-down)
1200 c2          7   2 (top-down)
1201 c3          5   5 (left-right)
1202 c4          3   8 (down-top)
1203 c5          9   7 (top-down)
1204
1205      26  23  (a > b)
1206
1207 53.5.7 Length of each edge is proportional to the difference between score(a) and score(b) at criterion c.
1208 53.5.8 Lemma: a is better than b implies a top-down crossing event and b is better than a implies down-top crossing ε
1209 Proof: If a is better than b in majority of the criteria then the path is more "top-down"-ish due to 53.5.4 (top-left
1210 53.5.9 Above variant of percolation boolean function returns 1 if path is top-down (a > b) else 0 if path is down-top
1211 53.5.10 Previous description is an equivalence reduction of percolation and judging two adversaries.
1212 53.5.11 To differentiate top-down and down-top left-right paths, comparator circuits (constant depth, polysize) and r
1213
1214
1215 53.6 (THEORY) Circuit for Percolation as a Judge Boolean Function
1216
1217 For an m * m grid with random edges, maximum length of the left-right path is m^2 (traverses all grid cells). Each bc
1218 - 1 if both x-axis coordinate of the leftmost ordered pair is 0 and x-axis coordinate of the rightmost ordered pair
1219 - else 0
1220 which requires comparators. Sorting networks of depth O((log n)^2 * n) and size O(n(log n)^2) exist for algorithms like E
1221 - Sorting network that sorts the coordinates left-right in NC1 or NC2
1222 - Comparator circuits in constant depth and polynomial size
1223 which together are in NC. This is non-uniform NC with advice strings as the circuit depends on percolation grid - e.g
1224
1225 Above percolation circuit based on Sorting networks is not optimal for arbitrarily large inputs. As per Noise Stabili
1226
1227
1228 53.7 (THEORY) P/Poly and P(Good) LHS and RHS - Karp-Lipton and Meyer's Theorems
1229
1230 P/poly is the circuit class of polynomial size with polynomial advice strings and unrestricted depth. Thus P/poly is
1231
1232 If RHS is simply NP (if depth restricted and unlikely for arbitrary number of electorate) then LHS is a P/poly algori
1233 EXPTIME version of this is Meyer's Theorem which states that if EXPTIME is in P/poly (which is the hardest case for P
1234
1235 References:
1236
1237
1238 53.7.1 Relation between NC and P/poly - http://cs.stackexchange.com/questions/41344/what-is-the-relation-between-nc-and-poly
1239 53.7.2 P/poly - https://en.wikipedia.org/wiki/P/poly
1240 53.7.3 Karp-Lipton Theorem - https://en.wikipedia.org/wiki/Karp%E2%80%93Lipton\_theorem
1241 53.7.4 NP in P/poly implies AM=MA - [Arvind, Vikraman; Köbler, Johannes; Schöning, Uwe; Schuler, Rainer (1995),] -
1242 53.7.5 BPP, PH, P/poly, Meyer's theorem etc., - http://www.cs.au.dk/~arnsfelt/CT10/scrivenotes/lecture9.pdf
1243 53.7.6 Descriptive Complexity - https://books.google.co.in/books?id=kW5Z00WnupkC&pg=PA177&lpg=PA177&dq=NC1/poly&source
1244 53.7.7 Non-uniform computation - https://courses.engr.illinois.edu/cs579/sp2009/slides/cc-s09-lect10.pdf
1245
1246
1247 53.8 (THEORY) An example Majority+SAT majority voting circuit, P(Good) convergence and some observations on Noise Sta
1248
1249 Let the number of voters be 8 (=2^3). Each voter has a boolean function of 3 variables - x1, x2 and x3. From Boolean F
1250
1251 If the RHS doesn't converge to 1 and thus is in BPP and Noise Stability of LHS is 100% (e.g by PRG choice of a percol
1252
1253 If the RHS has a perfect k-SAT boolean decision function for all voters, size of the circuit is super-polynomial and
1254
1255 If LHS of P(Good) is in NC/ log (Percolation as Judge boolean function) and RHS doesn't converge to 100% (i.e Majority
1256
1257 Subtlety 1: For single voter in RHS with a 3-SAT voter judge boolean function, RHS is NP-complete from voting complex
1258
1259 Subtlety 2: [Impagliazzo-Wigderson] theorem states that if there exists a decision problem with O(exp(n)) runtime and
1260
1261 NC/ log circuits can be made into a uniform circuits by hardwiring advice strings which are logarithmic size. There ar
1262
1263 References:
1264
1265 53.8.1 Pseudorandomness - [Impagliazzo-Wigderson] - http://people.seas.harvard.edu/~salil/pseudorandomness/pseudorandomness.pdf
1266 53.8.2 XOR Lemma [Yao] and [Impagliazzo-Wigderson] theorem - theory.stanford.edu/~trevisan/pubs/stv99stoc.ps
1267
1268
1269 53.9 (THEORY) Possible Scenarios in P(Good) LHS and RHS summation
1270
1271 53.9.1 LHS = RHS is 100% - LHS and RHS are equally efficient (and can be equated to get a lowerbound
1272 53.9.2 LHS is < 100% and RHS is < 100% - RHS is more efficient than LHS and both sides are in BP* classes

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1273 and LHS < RHS
1274 53.9.3 LHS is < 100% and RHS is < 100% - LHS and RHS are equally efficient (and can be equated to get a lowerbound
1275 and LHS = RHS
1276 53.9.4 LHS is < 100% and RHS is < 100% - LHS is more efficient than RHS and both sides are in BP* classes
1277 and LHS > RHS
1278 53.9.5 LHS is 100% and RHS is < 100% - LHS is more efficient than RHS. LHS is non-BP algorithm to RHS BP* algori
1279 53.9.6 LHS is < 100% and RHS is 100% - RHS is more efficient than LHS. RHS is non-BP algorithm to LHS BP* algori
1280
1281 -----
1282 53.10 (THEORY) Dictatorship, k-juntas testing and P(Good) circuit - simulation
1283 -----
1284 LHS of P(Good) is a pseudorandom choice judge boolean function. It has to be tested for dictatorship and k-junta prop
1285 the hardness of LHS. What is the probability of LHS pseudorandom choice being a dictator or k-junta boolean function?
1286 - PRG Choice outputs a Judge boolean function candidate for LHS.
1287 - Dictatorship or k-juntas testing algorithm is executed for this candidate PRG choice.
1288 Expected number of steps required for choosing a dictator via PRG is arrived at by Bernoulli trial. Repeated PRG choi
1289  $p(t) = (1-k/n)^{t-1}(k/n) = (n-k)^{t-1} * k/n^t$ 
1290
1291 If t is the random variable, expectation of t is:
1292  $E(t) = \sigma(t * p(t)) = \sigma((n-k)^{t-1} * tk/n^t)$ 
1293
1294 For a property testing algorithm running in  $O(q)$ , time required in finding a dictator or k-juntas is  $O(q * \sigma((n-k)^t))$ 
1295
1296 For k=0:
1297    $E(t) = 0$ 
1298 For k=1:
1299    $E(t) = \sigma((n-1)^{t-1} * t/n^t) = 1/n + (n-1)^2/n^2 + (n-1)^2*3/n^3 + \dots$ 
1300    $< 1/n + 2n/n^2 + 3n^2/n^3 + \dots$ 
1301    $= 1+2+3+\dots+n/n$ 
1302    $= n(n+1)/2n$ 
1303    $= (n+1)/2$ 
1304 Thus to find one dictator approximately  $(n+1)/2$  PRG expected choices are required. Above is not necessarily an exact
1305
1306 [Axiomatically k shouldn't be greater than 1 i.e there shouldn't be more than one dictator or juntas. Philosophical p
1307
1308 References:
1309 -----
1310 53.10.1 Dictatorship,k-juntas testing - [Oded Goldreich] - http://www.wisdom.weizmann.ac.il/~oded/PDF/pt-junta.pdf
1311
1312 -----
1313 (THEORY-*IMPORTANT*) 53.11 Hastad-Linial-Mansour-Nisan (HLMN) Theorem and Noise Stable boolean functions - Denoisific
1314 -----
1315 Hastad-Linial-Mansour-Nisan Theorem states that for a boolean function  $f: \{0,1\}^n \rightarrow \{0,1\}$  computed by circuit of size  $\leq$ 
1316 fourier coefficients for large  $S$  are epsilon-concentrated:
1317    $\sigma(\text{fourier_coeff}(S)^2) < \epsilon$  for  $|S| > t$  where  $t = O((\log s/\epsilon)^{(1/d-1)})$ .
1318 Above implies that:
1319    $t = O(\log s/\epsilon)^{(1/d-1)} = k * (\log s/\epsilon)^{(1/d-1)}$  for some constant k.
1320    $(t/k)^{(1/d-1)} = \log(s/\epsilon)$ 
1321    $s = \epsilon * 2^{(t/k)^{1/(d-1)}}$ 
1322 For a noisy boolean function  $f$  with rho probability of flip, the noise operator  $T$  is applied to the Fourier expansion
1323    $T(f) = \sigma(\rho^{|S|} * \text{fourier_coeff}(S) * \text{parity}(S))$  for  $S$  in  $[n]$  and each Fourier coefficient of  $T(f) = \rho^{|S|} * \text{fourier_coeff}(S)$ 
1324 From HLMN theorem, applying noise operator above (this needs to be verified) to noisy boolean function circuit Fourier
1325    $\text{if } \sigma([\rho^{|S|} * \text{fourier_coeff}(S)]^2) \leq \epsilon$ ,  $|S| > t$  where  $t = O((\log s/\epsilon)^{(1/d-1)})$ ,
1326   size  $s = \sigma([\rho^{|S|} * \text{fourier_coeff}(S)]^2) * 2^{(t/k)^{1/(d-1)}}$  substituting for epsilon and  $|S| > t$ .
1327   Thus size of the circuit exponentially depends on  $t$  - size of parity sets  $S$  in  $[n]$  -  $|S|$  - which can have max
1328
1329 If  $f$  is 100% noise stable, from Plancherel theorem:
1330    $\sigma(\rho^{|S|} * f(S)^2) = 1$ ,  $S$  in  $[n]$ 
1331 Stability can be written as:
1332    $\sigma_{S \leq t}(\rho^{|S|} * f(S)^2) + \sigma_{S > t}(\rho^{|S|} * f(S)^2) = 1$ 
1333    $[1 - \sigma_{S \leq t}(\rho^{|S|} * f(S)^2)] = \sigma_{S > t}(\rho^{|S|} * f(S)^2)$ 
1334 Since  $\rho < 1$ :
1335    $\epsilon = \sigma_{S \leq t}(\rho^{|S|} * f(S)^2) < \epsilon_{\text{stable}} = \sigma_{S > t}(\rho^{|S|} * f(S)^2)$ ,  $|S| > t$ 
1336    $\epsilon_{\text{stable}}$  can also be written as =  $\sigma_{S \leq t}(\rho^{|S|} * f(S)^2)$ ,  $|S| < t$ 
1337
1338    $s = \sigma(f(S)^2) * 2^{(t/k)^{1/(d-1)}}$ ,  $t = O((\log s/\epsilon)^{(1/d-1)})$ ,  $|S| > t$ 
1339    $s_{\text{stable}} = [1 - \sigma_{S \leq t}(\rho^{|S|} * f(S)^2)] * 2^{(t/k)^{1/(d-1)}}$ ,  $t = O((\log s_{\text{stable}}/\epsilon)^{(1/d-1)})$ ,  $|S| < t$ 
1340   (or)
1341    $s_{\text{stable}} = \sigma(\rho^{|S|} * \text{fourier_coeff}(S)^2) * 2^{(t/k)^{1/(d-1)}}$ ,  $t = O((\log s_{\text{stable}}/\epsilon)^{(1/d-1)})$ ,
1342    $s_{\text{stable}}$  is the size of the 100% noise stable circuit for  $f$ .
1343 From above,  $t$  with noise operator is:
1344    $t(\text{noise\_operator}) = O(\log s / \sigma(\rho^{|S|} * f(S)^2))$ ,  $|S| > t$  (or)
1345    $t(\text{noise\_operator}) = O(\log s / (1 - \sigma_{S \leq t}(\rho^{|S|} * f(S)^2)))$ ,  $|S| < t$ 
1346 which is substituted for  $t$  in  $s_{\text{stable}}$  above and  $t$  without noise operator is:
1347    $t = O(\log s / \sigma(f(S)^2))$ ,  $|S| > t$ 
1348 which implies that  $t(\text{noise\_operator}) > t$  since denominator summation of fourier coefficients is attenuated by  $\rho^{|S|}$ 
1349
1350 *Implication 1 of above: If RHS is in BPP (e.g a 3-SAT voter judge boolean function circuit with < 100% noise stabili
1351
1352 *Implication 2 of above: If LHS of P(Good) has BP.(NC/log) circuit due to <100% noise stability, with polynomial size
1353

```

1354 Points 53.4, 53.5, 53.6 and 53.7 describe P/poly, NC/poly and NC/log circuits for Percolation Boolean Functions subje
 1355
 1356 Noise sensitive NC/log percolation circuit in LHS of P(Good) is in BP(NC/log) which requires denoisification and dera
 1357
 1358 -----
 1359 (THEORY-*IMPORTANT*) 53.12 Hastad-Linial-Mansour-Nisan (HLMN) Theorem and Noise Stable boolean functions - Denoisific
 1360 -----
 1361 Above version derived by rewriting HLMN in terms of $s(\text{size})$ and $t(\text{size of fourier basis})$ is not too appealing. Basica
 1362 For $|S| > t$, $\text{Summation}(\text{fourier_coeff}(S)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1363 For Noise-operated Fourier Spectra, the summation is augmented with $\rho(\text{noise operator})$:
 1364 For $|S| > t$, $\text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1365 Applying Plancherel theorem and stability=1:
 1366 -----
 1367 | For $|S| < t$, $1 \cdot \text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1368 | $\Rightarrow [1 \cdot \text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2)] \cdot 2^{\frac{1}{d}-\frac{1}{20}-1} \leq \text{Size}$
 1369 -----
 1370 which is the circuit size lowerbound in terms of noise probability and fourier coefficients. As ρ increases from 0
 1371 size decreases, that is, low noise requires high circuit size. Partial Derivative of size bound wrt ρ :
 1372 $-\text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2) \cdot 2^{\frac{1}{d}-\frac{1}{20}-1} \leq \text{doe}(\text{Size})/\text{doe}(\rho)$
 1373 which points to exponential - in t and d - decrease in size (because $t=O(n)$ and $d=O(\text{function}(n))$ with linear increase
 1374 -----
 1375 | P(Good) binomial summation in its circuit version can not have polynomial size circuits
 1376 | when LHS and RHS converge with 100% noise stability.
 1377 -----
 1378 For example, if LHS is a percolation logdepth circuit and RHS is single voter with 3-SAT NP-complete circuit, when LHS
 1379 -----
 1380 LHS circuit size $\geq O(2^n \cdot \text{polylog}(n)) =$ superpolynomial, quasiexponential lowerbound, depth is $\text{polylog}(n)$
 1381 implying LHS percolation circuit could become superpolynomial sized when noise stability is 1 and not in NC despite t
 1382 -----
 1383 RHS circuit size $\geq O(2^n \cdot \frac{1}{d}) =$ higher superpolynomial, quasiexponential lowerbound, depth is arbitrary ,
 1384 and thus LHS and RHS circuits are equally efficient algorithms with differing circuit sizes. As RHS is NP-complete, L
 1385 [Open question: Does this imply superpolynomial size lowerbounds for NP and thus P != NP]
 1386 -----
 1387
 1388 Reference:
 1389 -----
 1390 53.12.1 Derandomizing BPNC - [Periklis Papakonstantinou] - http://iis.tsinghua.edu.cn/~papakons/pdfs/phd_thesis.pdf
 1391 53.12.2 Derandomization basics - [Salil] - Enumeration - <http://people.seas.harvard.edu/~salil/pseudorandomness/basic>
 1392 53.12.3 Simplified Hitting Sets Derandomization of BPP - [Goldreich-Vadhan-Wigderson] - <http://www.wisdom.weizmann.ac.il/~reni/pubs/derandomization.pdf>
 1393 53.12.4 Derandomizing BPNC - Existence of Hitting Set Generators for BPNC=NC - [Alexander E. Andreev, Andrea E.F.Clementi, Luca Trevisan] - <http://www.ma.huji.ac.il/~ehudf/courses/anal09/LMN.pdf>
 1394 53.12.5 Linial-Mansour-Nisan Theorem - Lemma 7 (Main Lemma) - <http://www.ma.huji.ac.il/~ehudf/courses/anal09/LMN.pdf>
 1395 For $|A| > t$, $\text{Summation}(\text{fourier_coeff}(A)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1396 53.12.6 The Computational Complexity Column [Allender-Clementi-Rolim-Trevisan] - theory.stanford.edu/~trevisan/pubs/elliptic.pdf
 1397 -----
 1398
 1399 53.13. (THEORY) Partial Derivative of Circuit size wrt ρ (noise probability) - increase in circuit size for Denoisi
 1400 -----
 1401 From 53.11 above, size of denoisified circuit from HMLN theorem, and Stability in terms of Fourier coefficients with
 1402 $s_{\text{stable}} = [1 - \sigma_{S < t}(\rho^{|S|} \text{fourier_coeff}(S)^2)] \cdot 2^{\frac{1}{d}-\frac{1}{20}}$, $t=O((\log s_{\text{stable}}/\epsilon)^{d-1})$, $|S|$
 1403 (or)
 1404 $s_{\text{stable}} = \sigma(\rho^{|S|} \text{fourier_coeff}(S)^2) \cdot 2^{\frac{1}{d}-\frac{1}{20}}$, $t=O((\log s_{\text{stable}}/\epsilon)^{d-1})$,
 1405 Lower bound of exponent increases as $\sigma(\rho^{|S|} \text{fourier_coeff}(S)^2)$ decreases in denominator of exponent subject to stability
 1406 $[1 - \sigma_{S < t}(\rho^{|S|} \text{fourier_coeff}(S)^2)] = \sigma_{S > t}(\rho^{|S|} \text{fourier_coeff}(S)^2)$
 1407 which implies that $\sigma_{S > t}(\rho^{|S|} \text{fourier_coeff}(S)^2)$ decreases when $\sigma_{S < t}(\rho^{|S|} \text{fourier_coeff}(S)^2)$ increases. This is Consequenc
 1408 -----
 1409 Partial derivative of Circuit size wrt to ρ can be derived as:
 1410 $\delta_s/\delta_\rho = \sigma_{S > t}(|S| \rho^{|S|-1} \text{fourier_coeff}(S)^2) / (1 - \sigma_{S < t}(\rho^{|S|} \text{fourier_coeff}(S)^2))$ where δ_s is
 1411 -----
 1412 53.14. (THEORY) Hastad-Linial-Mansour-Nisan Theorem, Circuit size, Noise Stability and BP* classes
 1413 -----
 1414 Percolation circuit defined previously has:
 1415 - Sorting Network for creating path sequentially on grid (NC logdepth and polysize)
 1416 - Comparators (Constant depth and polysize) are required for comparing the leftmost and rightmost coordinates.
 1417 Together Percolation is in non-uniform NC. This circuit depends on number of points on the left-right path which is p
 1418 Therefore percolation is in NC/poly because size of list of advice strings could be $O((n^2) \log(n^2))$ and it may not h
 1419 -----
 1420 From Linial-Mansour-Nisan Theorem - Lemma 7 (Main Lemma) - <http://www.ma.huji.ac.il/~ehudf/courses/anal09/LMN.pdf>:
 1421 For $|A| > t$, $\text{Summation}(\text{fourier_coeff}(A)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1422 With noise operator, noise stability=1 from Plancherel's theorem:
 1423 -----
 1424 | For $|S| < t$, $1 \cdot \text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1425 | Corollary: For $|S| > t$, $\text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2) \leq 2^*(\text{Size})^2^{\frac{1}{d}-\frac{1}{20}}$
 1426 | $\Rightarrow [1 \cdot \text{Summation}(\rho^{|S|} \text{fourier_coeff}(S)^2)] \cdot 2^{\frac{1}{d}-\frac{1}{20}-1} \leq \text{Size}$
 1427 -----
 1428 When denoisified, $\rho=0$ and lowerbound for size:
 1429 $[1 - (0^0 \cdot f(\phi))^{2+0+0+...}] \cdot 2^{\frac{1}{d}-\frac{1}{20}-1} \leq \text{size}$
 1430 $[1 - f(\phi)^2] \cdot 2^{\frac{1}{d}-\frac{1}{20}-1} \leq \text{size}$ (as all other coefficients vanish)
 1431 when $t=n$, the size is lowerbounded by :
 1432 $[1 - f(\phi)^2] \cdot 2^{\frac{1}{d}-\frac{1}{20}-1}$

1435 which is superpolynomial. This implies an NC/poly polysize circuit when denoised becomes $O(2^{(n^{(1/\text{polylog}(n))}/20)})$

1436

1437 From the table that describes relation between Noise and Error(BP* and PP) in 14 previously, it is evident that Noise

1438 if following is drawn as a Venn Diagram i.e. Noise stability solves just a fraction of total error, and remaining req

1439 In other words, Noisy circuit could be error-free and Noise-free circuit could have error.

x	$f(x) = f(x/e)$	$f(x) \neq f(x/e)$ Noise
x in L, x/e in L	No error	Error
x in L, x/e not in L	Error	No error if $f(x)=1, f(x/e)=0$ else Error
x not in L, x/e in L	Error	No error if $f(x)=0, f(x/e)=1$ else Error
x not in L, x/e not in L	No error	Error

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1454 Noise percolation circuit in P(Good) summation converges in noise stability regime:

1455 $\text{Pr}[f(w(n)) \neq f(w(n)/e)] = 0, e=1/(\alpha^{4n^2})$

1456 $n \rightarrow \infty$

1457 Infinite $f(n)$ is representable as Non-uniform NC/poly circuit though undecidable because turing machine computing the

1458

1459 For a 3-CNF SAT boolean function with noise, size of circuit is lowerbounded as:

1460 $[1-\text{Summation}(\rho^{|S|} \cdot \text{fourier_coeff}(S)^2)] * 2^{((t^{(1/d)})/20)-1} \leq \text{Size}$, for constant depth d.

1461 For $\rho=1$,

1462 $[1-\text{Summation}(\text{fourier_coeff}(S)^2)] * 2^{((t^{(1/d)})/20)-1} \leq \text{Size}$, for constant depth d, $|S| < t$.

1463

1464 Gist of the above:

1465 53.14.1 Size of percolation logdepth circuit (with noise) $\rho=1$:

1466 $(f([n])^2) * 2^{(n^{(1/\text{polylog}(n-1))/20})-1} \leq \text{size}$

1467 53.14.2 Size of depth d circuit (with noise) $\rho=1$:

1468 $(f([n])^2) * 2^{((n-1)^{(1/d)/20})-1} \leq \text{size}$

1469 53.14.3 Size of percolation logdepth circuit (with noise) $\rho=0$:

1470 $(1-f([phi])^2) * 2^{(n^{(1/\text{polylog}(n))/20})-1} \leq \text{size}$, phi is empty set

1471 53.14.4 Size of depth d circuit (with noise) $\rho=0$:

1472 $(1-f([phi])^2) * 2^{(n^{(1/d)/20})-1} \leq \text{size}$, phi is empty set

1473

1474

1475 53.15 (THEORY) Special Case of HLMN theorem for PARITY as 3-SAT and counterexample for polynomial circuit size

1476

1477 From HLMN theorem:

1478 $\text{Summation}(\text{fourier_coeff}(S)^2) * 2^{((t^{(1/d)})/20)-1} \leq \text{Size}$, for constant depth d, $|S| > t$.

1479 When $t=n-1$, fourier series has only coefficient for the parity set that has all variables:

1480 $\text{fourier_coeff}([n])^2 * 2^{((n-1)^{(1/d)/20})-1} \leq \text{size}$, for constant depth d.

1481 For a circuit of size polynomial (n^k) and depth 3:

1482 $\text{summation}(\text{fourier_coeff}([n])^2) \leq n^k / 2^{((t^{(1/3)})/20)-1}$.

1483 and for $t=n-1$:

1484 $\text{fourier_coeff}([n])^2 \leq n^k / 2^{((n-1)^{(1/3)/20})-1}$.

1485 From definition of fourier coefficients:

1486 $\text{fourier_coeff}([n]) = \text{summation}(f(x) * (-1)^{\text{parity}(x)}) / 2^n$ for all $x \in \{0,1\}^n$

1487 Maximum of $\text{fourier_coeff}([n])$ occurs when $f(x)=1$ for $(-1)^{\text{parity}(x)} = 1$ and when $f(x)=-1$ for $(-1)^{\text{parity}(x)} = -1$ to

1488 $\text{Maximum}(\text{fourier_coeff}([n])) = 2^n / 2^n = 1$ (this implies all other fourier coefficients are zero)

1489 Which happens when $f(x)$ is equivalent to Parity function.

1490 An example PARITY as 3-CNF SAT from DIMACS32 XORSAT [Jing Chao Chen - <http://arxiv.org/abs/cs/0703006>] that computes F

1491 $(x1 \vee \neg x2 \vee \neg x3) \wedge (\neg x1 \vee x2 \vee \neg x3) \wedge (\neg x1 \vee \neg x2 \vee x3) \wedge (x1 \vee x2 \vee x3)$

1492 Previous PARITY SAT accepts odd parity strings. Complementing variables in each clause makes it accept even parity:

1493 $(\neg x1 \vee x2 \vee x3) \wedge (x1 \vee \neg x2 \vee x3) \wedge (x1 \vee x2 \vee \neg x3) \wedge (\neg x1 \vee \neg x2 \vee \neg x3)$

1494 Assumption: PARITY as 3-CNF SAT has polynomial size.

1495 PARITY 3-SAT is satisfied by odd parity bit strings and is NP-complete because this is search version of parity - it

1496 $\Rightarrow 1^2 \leq n^k / 2^{((n-1)^{(1/3)/20})-1}$ which is a contradiction to assumption (denominator is exponential) that F

1497

1498 From above, for some circuit size of PARITY as 3-CNF SAT, there exists $t (= 0(n))$ such that:

1499 $2^{((t^{(1/3)/20})-1)} \leq \text{size} / \text{summation}(f(S)^2)$, $|S| > t$

1500 $2^{((t^{(1/3)/20})-1)} \leq \text{size}$ (for all $t < n-1$, fourier coefficients of PARITY 3-SAT are 0, and this bound is m

1501 i.e for all values of t , circuit size is bounded from below by a quantity exponential in function of n (which could be t)

1502

1503 (How can a special case of NP-complete problem have superpolynomial size circuits? Is this a counterexample and thus

1504

1505 References:

1506

1507 53.15.1 Circuit Complexity Lecture notes - [Uri Zwick] - <http://cs.tau.ac.il/~zwick>

1508 53.15.2 Lecture notes - [Nader Bshouty] - <http://cs.technion.ac.il/~bshouty>

1509

1510

1511 53.16 (THEORY) P/poly, Percolation and PARITY as 3-CNF SAT in 53.15

1512

1513 53.16.1 NP in P/poly (NP having polynomial size circuits) implies AM=MA and PH collapses to $\Sigma_2 \wedge \Pi_2$.

1514 53.16.2 PARITYSAT in 53.15 which is a special case of NP-complete has superpolynomial size circuits.

1515 53.16.3 If Percolation is in NC/poly and both LHS and RHS of P(Good) converge to 100% noise stability, does it imply

1516 arbitrary circuit size in RHS? In other words what does it imply when 2 circuits of varying size have equal stability
 1517
 1518
 1519 53.16.3.1 If equal error (NoiseStability +/- delta) with different circuit sizes implies a lowerbound:
 1520
 1521 There is an inherent conflict between 53.16.1, 53.16.3 which are conditions for polynomial size circuits for NP and 5
 1522 - LHS of P(Good) is percolation NC/poly circuit in 100% noise stability regime.
 1523 - RHS of P(Good) is non-percolation circuit of arbitrary size (e.g. DC circuit of exponential size , superpol
 1524 - LHS NC/poly 100% noise stability implies a lowerbound when RHS (e.g superpolynomial size NP circuit from 53
 1525 - the individual voter error/stability cannot be uniform 0.5 or 1 across the board for all voters - voters ha
 1526 - varied stability/sensitivity per voter implies RHS majority voting is Poisson Distribution.
 1527 - for probabilities other than 0.5 and 1, RHS P(good) summation becomes hypergeometric series requiring non-t
 1528 - This assumes that RHS does not have a boolean function that is 100% noise stability regime similar to LHS F
 1529 - Superpolynomial size for NP-complete PARITY3SAT (kind of a promise problem) implies P != NP and P != NP imp
 1530 In other words a democratic decision making which does not involve percolation is never perfect and thus BKS conjectu
 1531
 1532
 1533
 1534 53.16.3.2 If equal error (NoiseStability +/- delta) with different circuit sizes doesn't imply a lowerbound:
 1535
 1536 - LHS of P(Good) is percolation NC/poly circuit in 100% noise stability regime.
 1537 - RHS of P(Good) is of arbitrary size (e.g. superpolynomial size NP circuit from 53.16.2).
 1538 - LHS NC/poly 100% noise stability doesn't imply a lowerbound when RHS (e.g superpolynomial size NP circuit f
 1539
 1540
 1541 53.17 (THEORY) Oracle results and P=NP and PH
 1542
 1543 From [Baker-Gill-Solovay] there are oracles A and B such that P^A = P^B and P^A != P^B implying natural proofs involv
 1544
 1545
 1546 53.18 (THEORY) P(Good) circuit special case counterexample in PH collapse
 1547
 1548 LHS of P(Good) - a sigma(p,k) hard (could be dictatorial or PRG) circuit with 100% (noise stability +/- delta) (assum
 1549 RHS of P(Good) - a sigma(p,k+1) hard majority voting circuit with 100% (noise stability +/- delta) (assuming such exi
 1550
 1551 If above converging P(good) LHS and RHS imply a lowerbound , LHS sigma(p,k) lowerbounds RHS sigma(p,k+1) implying PH
 1552 The matrix of noise versus BPP in 53.14 and 14 imply noise and BPP intersect, but if only classes in (sigma(p,k) - BF
 1553
 1554 Equating sigma(p,k) with sigma(p,k+l) is probably the most generic setting for P(Good) circuits discounting arithmetic
 1555
 1556 Example sigma(p,k)-complete QBFSAT(k) boolean function:
 1557 there exists x1 for all x2 there exists x3 ... QBF1(x1,x2,x3,...,xk)
 1558
 1559 Example sigma(p,k+1)-complete QBFSAT(k+1) boolean function:
 1560 there exists x1 for all x2 there exists x3 ... QBF2(x1,x2,x3,...,xk,x(k+1))
 1561
 1562
 1563 53.19 (THEORY) Depth Hierarchy Theorem for P(Good) circuits
 1564
 1565 Average case Depth Hierarchy Theorem for circuits by [Rossman-Servedio-Tan] - <http://arxiv.org/abs/1504.03398> - state
 1566
 1567
 1568 53.20 (THEORY) Ideal Voting Rule
 1569
 1570 [Rousseau] theorem states that an ideal voting rule is the one which maximizes number of votes agreeing with outcome
 1571
 1572
 1573 53.21 (THEORY) Plancherel's Theorem, Stability polynomial and Lowerbounds in 53.18
 1574
 1575 Stability polynomial can be applied to QBFSAT(k) and QBFSAT(k+1) in 53.18.
 1576
 1577 By Plancherel's Theorem, Stability of a boolean function with noise rho is written as polynomial in rho:
 1578 Stability(f) = sigma(rho^|S|*f(S)^2) , S in [n]
 1579 which can be equated to 1 to find roots of this polynomial - noise probabilities - where 100% stability occurs.
 1580
 1581 From HLMN theorem for sigma(p,k)-complete QBFSAT(k):
 1582 sigma(f(A1)^2) <= 2*(M1)*2^(-t1^(1/d1)/20) , |A1| > t1
 1583
 1584 From HLMN theorem for sigma(p,k+1)-complete QBFSAT(k+1):
 1585 sigma(f(A2)^2) <= 2*(M2)*2^(-t2^(1/d2)/20) , |A2| > t2
 1586
 1587 When noise stability is 100%:
 1588 Stability(QBFSAT(k)) = sigma(rho1^|S1|*f(S1)^2) = 1, S1 in [n]
 1589 Stability(QBFSAT(k+1)) = sigma(rho2^|S2|*f(S2)^2) = 1, S2 in [n]
 1590 where rho1 and rho2 are variables each in the polynomial for QBFSAT(k) and QBFSAT(k+1). Solving these polynomials giv
 1591
 1592 Above deduction on PH collapse and possible PH-completeness contradicts 53.15 counterexample for NP having superpoly
 1593 - Equal decision error (stability +/- delta) does not imply lowerbound.
 1594 - Roots of sigma(rho^|S|*f(S)^2) - 1 = 0 can only be complex with Re+Im parts and can't be real.
 1595 - sigma(rho^|S|*f(S)^2) - 1 = 0 is zero polynomial where all coefficients are zero.
 1596 - PH-collapse does not imply PH-completeness.

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1597 Stability polynomial above with rho as variable can be applied to any circuit to find the noise probabilities where 1
1598
1599
1600
1601
1602 54(THEORY). Would the following experimental gadget work? It might, but impractical:
1603 A voter gadget spawns itself into liker, disliker and neutral parallel threads on an entity to be judged. The neutral
1604
1605 55(THEORY). Evocation is a realworld everyday phenomenon - a word reminding of the other. Positive thought chooses th
1606
1607 56(THEORY). A crude way to automatically disambiguate is to lookup the corresponding class stack and analyze only bou
1608
1609 57(THEORY). Thus Sentiment Mining techniques can be used for the above hypergraph to get the overall sentiment of the
1610
1611 58(THEORY). Thus not only documents but also events in human life can be modelled as above hypergraph to get a graphi
1612
1613 #####59. Initial Design Notes for - Mundane Predictive Model:
1614 #####
1615
1616 - (FEATURE - DONE) DecisionTree, NaiveBayes and SVM classifiers and horoscope encoders are already in the AstroInfer
1617 - (FEATURE - DONE) Encode the dataset which might be USGS or NOAA(Science on a Sphere) datasets or anyother dataset a
1618 - (FEATURE - DONE) Above gives encoded horoscope strings for all classes of mundane events in both Zodiacial and Ascer
1619 - (FEATURE - DONE) Above set is a mix of encoded strings for all events which can be classified using one of the clas
1620 - (FEATURE - DONE) For each class the set of encoded horo strings in that class can be pairwise or multiple-sequence
1621 - (FEATURE - DONE) There are two sets for each class after running the classifiers - one set is AscendantRelative and
1622 - (FEATURE - DONE) The above steps give the mined astronomical patterns for all observed mundane events - Pattern_Mur
1623
1624
1625 60. (FEATURE - DONE) Above has implemented a basic Class and Inference Model that was envisaged in 2003. Class is the
1626
1627
1628 61. (THEORY) Now on to mining the classics for patterns: For all classes of events, running the classifier partitions
1629
1630 62. (THEORY) Thus correlation of the two sets *_Observed_* and *_Classic_* (each set has 2 subsets) for percentage si
1631
1632 63. (THEORY and IMPLEMENTATION) More importantly, for example, if a non-statistical,astrological model of rainfall i
1633
1634 64. (FEATURE - DONE-related to 65 and 139) Integrate AstroInfer,USB-md,KingCobra and VIRGO into an approximately inte
1635 USB-md Design Document: http://sourceforge.net/p/usb-md/code-0/HEAD/tree/USBmd\_notes.txt
1636 VIRGO Design Document: http://sourceforge.net/p/virgo-linux/code-0/HEAD/tree/trunk/virgo-docs/VirgoDesign.txt
1637 KingCobra Design Document: http://sourceforge.net/p/kcobra/code-svn/HEAD/tree/KingCobraDesignNotes.txt
1638 This AsFer+USBmd+VIRGO+KingCobra would henceforth be known as "Krishna iResearch Intelligent Cloud OS - NeuronRain "
1639
1640 65. (THEORY and IMPLEMENTATION) Related to point 64 - Software Analytics - source code and logs analytics - related t
1641
1642 AsFer Python -----> Boost::Python C++ Extension -----> VIRGO memory system calls -----> VIRGO Linux Kerne
1643   \/
1644   |
1645 -----<----- AsFer Python -----> CPython Extensions -----> VIRGO memory system calls -----> VIRGO Linux Kernel Memory
1646   \/
1647   |
1648 -----<----- AsFer Python -----> VIRGO SATURN program analyzer .dot files -----> Spark ----> Cyclomatic Complexity
1649
1650
1651 -----
1652 References:
1653 -----
1654 65.1 Analytics of Device Driver code - http://research.microsoft.com/en-us/groups/sa/drivermine\_asplos14.pdf
1655 65.2 Logging - http://research.microsoft.com/en-US/groups/sa/loggingpractice.pdf
1656 65.3 Law of leaky abstraction - http://www.joelonsoftware.com/Articles/LeakyAbstractions.html
1657 65.4 Function Point Analysis - http://www.bfpuug.com.br/Artigos/Albrecht/MeasuringApplicationDevelopmentProductivity
1658 65.5 Function Point Analysis and Halstead Complexity Measures - https://en.wikipedia.org/wiki/Halstead\_complexity\_me
1659 65.6 Cyclomatic Complexity of a Program - Euler Characteristic of program flow graph (E - V + 2) - Approximate code
1660
1661
1662 66. (THEORY) Encoding a document with above Hypergraph of Class stack vertices and Hyperedges - This hypergraph of cc
1663
1664 67. An automaton or Turing machine model for data or voice (or musical) samples - Voice samples or musical notations
1665
1666 (FEATURE - DONE) 68. Music Pattern Mining - Computational Music - Alternatively, a Discrete Fourier Transform on a se
1667
1668 -----
1669 References:
1670 -----
1671 68.1 https://ccrma.stanford.edu/~jos/st/
1672
1673 69. (FEATURE - Audacity FFT - DONE) Music Pattern Mining - Experimental Idea of previous two points is to mine patter
1674      69.1 FFT of the two audio files were done by Audacity and frequency domain files were obtained with sampling
1675      69.2 FFTs of these two have been committed in music_pattern_mining/. Similarity is observed by peak decibel f
1676
1677 -----

```

```

1678 70-79 (THEORY - EventNet Implementation DONE) EventNet and Theoretical analysis of Logical Time:
1679 -----
1680
1681 70. In addition to Concept wide hypergraph above, an interesting research could be to create an EventNet or events cc
1682
1683 71. Each event node in the node which is a set as above, can have multiple outcomes and hence cause multiple effects.
1684
1685 72. If the EventNet is formulated as a Dynamic Graph with cycles instead of Static Graph as above where there causal
1686
1687 73. EventNet can be partitioned into "Past", "Present" and "Future" probably by using some MaxFlow-MinCut Algorithms.
1688
1689 74. A recreational riddle on the EventNet: Future(Past) = Present. If the Future is modelled as a mathematical functi
1690
1691 75. Conjecture: Undirected version of EventNet is Strongly Connected or there is no event in EventNet without a cause
1692
1693 76. Events with maximum indegree and outdegree are crucial events that have deep impact in history.
1694
1695 77. Events in each individual entity's existence are subgraphs of universal EventNet. These subgraphs overlap with ea
1696
1697 78. There is an implicit time ordering in EventNet due to each causation edge. This is a "Logical Clock" similar to L
1698
1699 79. EventNet can also be viewed as a Bayesian Network.

1700 -----
1701 80. (THEORY) Mining EventNet for Patterns:
1702 -----
1703 As an old saying goes "history repeats itself". Or does it really? Are there cycles of events? Such questions warrant
1704
1705 Frequent Subgraph Mining of above EventNet (i.e whether a subgraph "repeats" with in the supergraph) as mentioned in
1706
1707 There is a striking resemblance of EventNet to sequence mining algorithm CAMLS - a refined Apriori algorithm - (http://
1708
1709
1710 -----
1711 81-86. (THEORY) Fractal nature of events:
1712 -----
1713 81. Are events self-similar or exhibit fractal nature? This as in item 71, needs mining the event nodes which are set
1714
1715 82. EventNet is a Partial Order where there may not be edges of causality between some elements. Thus a Topological S
1716
1717 83. EventNet on history of events in the universe is quite similar to Directed Acyclic Graph based Scheduling of task
1718
1719 84. In the above EventNet, each node which is a set can indeed be a graph also with freewill interactions amongst the
1720
1721 85. Similar to Implication graphs as Random Growth Graphs, EventNet also qualifies as a Random Growth Network as ever
1722
1723 86. Regularity Lemma can be used as a tool to test Implication and EventNet Random Growth Graphs - specifically seems
1724
1725 ****
1726 87. COMMIT RELATED NOTES
1727 ****
1728
1729 (FEATURE- DONE) commits as on 3 September 2013
1730 -----
1731 DecisionTree, NaiveBayes and SVM classifier code has been integrated into AstroInfer toplevel invocation with boolean
1732
1733 (FEATURE- DONE) commits as on 6 September 2013
1734 -----
1735 In addition to USGS data, NOAA Hurricane dataset HURDAT2 has been downloaded and added to repository. Asfer Classifie
1736
1737 (FEATURE- DONE) commits as on 12 September 2013
1738 -----
1739 1.asfer_dataset_segregator.py and asfer_dataset_segregator.sh - Python and wrapper shell script that partitions the p
1740
1741 2.DateTimeLongLat data for all datasets within an event class (text file) need to be collated into a single asfer.enc
1742
1743 (FEATURE- DONE) commits as on 2 November 2013
1744 -----
1745 Lot of commits for implementation of Discrete Hyperbolic Factorization with Stirling Formula Upperbound (http://source:
1746 1) Multiple versions of Discrete Hyperbolic Factorization uploaded in http://sites.google.com/site/kuja27/
1747 2) Handwritten by myself - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicFactorization
1748 3) Latex version - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieve/
1749
1750
1751 (FEATURE- DONE) commits as on 20 November 2013 and 21 November 2013
1752 -----
1753 1. Lots of testing done on Discrete Hyperbolic Factorization sequential implementation and logs have been added to re
1754
1755 2. An updated draft of PRAM NC version of Discrete Hyperbolic Factorization has been uploaded at:
1756 http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization\_PRAM\_
1757
1758 3. Preliminary Design notes for CRCW PRAM implementation of the above is added to repository at: http://sourceforge.r

```

1759
 1760
 1761
 1762 88. Tagging as on 16 December 2013
 1763
 1764 AsFer version 12.0 and VIRGO version 12.0 have been tagged on 6 December 2013 (updated the action items above).
 1765
 1766 (THEORY) 89. More reference URLs for Parallel RAM design of above NC algorithm for Discrete Hyperbolic Factorization
 1767
 1768 1.http://arxiv.org/pdf/1202.6575.pdf?origin=publication_detail
 1769 2.https://lectures.informatik.uni-freiburg.de/portal/download/3/6951/thm15%20-%20parallel%20merging.ppt (Ranks of el
 1770 3.http://cs.brown.edu/courses/csci2560/syllabus.html (Lecture Notes on CREW PRAM and Circuit Equivalence used in the
 1771 Hyperbolic Factorization above - http://cs.brown.edu/courses/csci2560/lectures/lect.24.pdf)
 1772 4.http://cs.brown.edu/courses/csci2560/lectures/lect.22.ParallelComputationIV.pdf
 1773 5.http://www.cs.toronto.edu/~bor/Papers/routing-merging-sorting.pdf
 1774 6.http://www.comgeom.com/~piyush/teach/AA09/slides/lecture16.ppt
 1775 7.Shift-and-subtract algorithm for approximate square root computation implemented in Linux kernel (http://lxr.free-e
 1776 8.http://research.sun.com/pls/apex/f?p=labs:bio:0:120 - Guy Steele - approximate square root algorithm
 1777 9.http://cstheory.stackexchange.com/questions/1558/parallel-algorithms-for-directed-st-connectivity - related theor
 1778 10.PRAM and NC algorithms - http://www.cs.cmu.edu/afs/cs/academic/class/15750-s11/www/handouts/par-notes.pdf
 1779 11. An Efficient Parallel Algorithm for Merging in the Postal Model - http://etrij.etri.re.kr/etrij/journal/getPublis
 1780 12. Parallel Merge Sort - http://www.inf.fu-berlin.de/lehre/SS10/SP-Par/download/parmerge1.pdf
 1781 13. NC and PRAM equivalence - www.cs.tau.ac.il/~safra/ACT/CCandSpaceB.ppt
 1782 14. Extended version of BerkmanSchieberVishkin ANSV algorithm - http://www1.cs.columbia.edu/~dany/papers/highly.ps.Z
 1783 15. Structural PRAM algorithms (with references to NC) - http://www.umiacs.umd.edu/users/vishkin/PUBLICATIONS/icalp91
 1784 16. Parallel Algorithms FAQ - NC, RAM and PRAM - Q24 - http://nptel.ac.in/courses/106102114/downloads/faq.pdf
 1785
 1786 17. Definitions related to PRAM model - http://pages.cs.wisc.edu/~tvrdik/2/html/Section2.html - Input to PRAM is N ite
 1787
 1788 18. Reduction from PRAM to NC circuits - http://web.cse.ohio-state.edu/~gurari/theory-bk/theory-bk-sevense6.html#Q1-8
 1789
 1790 19. Length of input instance in PRAM (n or N) - http://web.cse.ohio-state.edu/~gurari/theory-bk/theory-bk-sevense2.ht
 1791
 1792 20. Quoted abstract - "... The all nearest smaller values problem is defined as follows. Let A = (a1 ; a2 ; : : : ; a
 1793
 1794 21. SIMULATE_RAM subcircuit in point 18 - Number of bits allowed per PRAM cell in PRAM to NC reduction - http://hall.
 1795
 1796
 1797 -----
 1798 (THEORY) 90. Some notes on extensions to Integer partitions and Hash Functions
 1799 (https://sites.google.com/site/kuja27/IntegerPartitionAndHashFunctions.pdf?attredirects=0)
 1800
 1801 1. Riemann sums (discrete approximation of Riemann integral) of all the functions corresponding to the hash functions
 1802
 1803 2. Hardy-Ramanujan asymptotic bound for partition function p(n) is $\sim 0(e^{(pi*sqrt(0.66*n))}/(4*1.732*n))$ which places a
 1804
 1805 3. If m-sized subsets of the above $0(m!*e^{(sqrt(n))}/n)$ number of hash functions are considered as a (k,u)-universal c
 1806
 1807 4. Thus deriving a bound for number of possible hash functions in terms of number of keys and values could have bear
 1808
 1809 5. Birthday problem and Balls and Bins problem - Since randomly populating m bins with n balls and probability of pec
 1810
 1811 6. Restricted partitions which is the special case of integer partitions has some problems which are NP-complete. Mor
 1812
 1813 7. The special of case of majority voting which involves integer partitions described in https://sites.google.com/sit
 1814
 1815 8. Thus Majority voting can be shown to be NP-complete in 2 ways:
 1816 8.1 by Democracy circuit (Majority with SAT) in http://sourceforge.net/projects/acadpdrafts/files/Implicatio
 1817 8.2 by reduction from an NP-hard instance of Restricted Partition problem like Money changing problem for Maj
 1818
 1819 9. Infact the above two ways occur in two places in the process of democratic voting: The democracy circuit is needed
 1820
 1821 10. Point 8.2 above requires a restricted partition with distinct non-repeating parts. There are many results on this
 1822
 1823 11. An interesting manifestation of point 10 is that nothing in real-life voting precludes a tie and enforces a restr
 1824
 1825 12. Counting Number of such restricted partitions is a #P-complete problem - https://www.math.ucdavis.edu/~deloera/T
 1826
 1827 13. If a Hash table is recursive i.e the chains themselves are hashtables and so on... then this bijectively correspc
 1828
 1829 14. If the hash table chains are alternatively viewed as Compositions of an integer (ordered partitions) then there a
 1830
 1831 15. In the summation over all parts of partitions derived in https://sites.google.com/site/kuja27/IntegerPartitionAnc
 1832
 1833 16. Logarithm of above summation then is equal to $(n-1)$ and thus can be equated to any partition of n. Thus any parti
 1834
 1835 -----
 1836 91. Updated drafts on Integer partitions and hash function (with points in 80 above) , Circuits for Error probability
 1837
 1838 1. https://sites.google.com/site/kuja27/IntegerPartitionAndHashFunctions_2014.pdf?attredirects=0&d=1
 1839 2. https://sites.google.com/site/kuja27/CircuitForComputingErrorProbabilityOfMajorityVoting_2014.pdf?attredirects=0&c

```

1840
1841
1842
1843
1844 92. Reference URLs for restricted integer partitions with distinct parts
1845 (for http://sites.google.com/site/kuja27/IntegerPartitionAndHashFunctions_2014.pdf?attredirects=0&d=1)
1846 1. Generating function - http://math.berkeley.edu/~mchaiman/math172-spring10/partitions.pdf
1847 2. Schur's theorem for asymptotic bound for number of denumerants - http://en.wikipedia.org/wiki/Schur's_theorem
1848 3. Frobenius problem - http://www.math.univ-montp2.fr/~ramirez/Tenerif3.pdf
1849 4. Locality Sensitive Hashing (that groups similar keys into a collision bucket chain using standard metrics like Ham
1850 5. Locality Sensitive Hashing and Lattice sets (of the diophantine form  $a1*x1+a2*x2+...+an*xn$ ) - http://hal.inria.fr
1851 6. Minhash and Jaccard similarity coefficient - http://en.wikipedia.org/wiki/MinHash#Jaccard_similarity_and_minimum_t
1852
1853 (THEORY) 93. Reduction from Money Changing Problem or 0-1 Integer LP to Restricted Partitions with distinct parts
1854
1855 If the denominations are fixed as 1,2,3,4,5,...,n then the denumerants to be found are from the diophantine equation
1856  $a1*1 + a2*2 + a3*3 + a4*4 + a5*5 + ... + an*n$ 
1857 (with  $ai = 0$  or 1). GCD of all  $ai$ s is 1. Thus Schur's theorem for MCP or Coin Problem applies.
1858 Integer 0-1 LP NP-complete problem can also be reduced to above diophantine format instead of MCP. Finding one such  $ai$ 
1859 boolean values is then NP-complete and hence finding one partition with distinct non-repeating parts is NP-complete (majority vote).
1860
1861
1862 (FEATURE- DONE) 94. Commits as on 23 April 2014
1863
1864 Updated pgood.cpp with some optimizations for factorial computations and batched summation to circumvent overflow to
1865 For Big decimals IEEE 754 with 112+ bits precision is needed for which boost::multiprecision or java.math.BigDecimal
1866
1867
1868 (FEATURE- DONE) 95. Commits as on 7 July 2014
1869
1870 Initial implementation of a Chaos attractor sequence implementation committed to repository.
1871
1872
1873 (FEATURE- DONE) 96. Commits as on 8 July 2014
1874
1875 Python-R (rpy2) code for correlation coefficient computation added to above Chaos attractor implementation.
1876
1877
1878 (FEATURE- DONE) 97. Time Series Analysis - Commits as on 9 July 2014
1879
1880 DJIA dataset, parser for it and updated ChaosAttractor.py for chaotic and linear correlation coefficient computation
1881 have been committed.
1882
1883
1884 (FEATURE- DONE) 98. Commits as on 10 July 2014
1885
1886 Python(rpy2) script for computing Discrete Fourier Transform for DJIA dataset has been added (internally uses R). [py
1887
1888
1889 (FEATURE- DONE) 99. Commits as on 11 July 2014
1890
1891 Python(rpy2) script for spline interpolation of DJIA dataset and plotting a graph of that using R graphics has been a
1892
1893
1894 (FEATURE- DONE) 100. Commits as on 15 July 2014 and 16 July 2014
1895
1896 Doxygen documentation for AsFer, USBmd, VIRGO, KingCobra and Acadpdrafts have been committed to GitHub at https://gi
1897
1898
1899 (FEATURE- DONE) 101. Commits as on 23 July 2014
1900
1901 Draft additions to http://arxiv.org/pdf/1106.4102v1.pdf are in the Complement Function item above. An R graphics rpy2
1902
1903
1904 (FEATURE - THEORY - Visualizer Implementation DONE) 102. Dense Subgraphs of the WordNet subgraphs from Recursive Glos
1905 http://arxiv.org/abs/1006.4458 and http://www.nist.gov/tac/publications/2010/participant.papers/CMI_IIT.proceedings.p
1906
1907 102.1 http://kylescholz.com/projects/wordnet/
1908 102.2 http://www.visuwords.com
1909 102.3 http://www.visualthesaurus.com/browse/en/Princeton%20WordNet
1910
1911
1912
1913 103. AsFer version 14.9.9 release tagged on 9 September 2014
1914
1915
1916 (FEATURE- DONE) 104. Commits as on 9 October 2014
1917
1918 Initial python script implementation for Text compression committed with logs and screenshot. Decompression is still
1919
1920

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1921 (FEATURE- DONE) 105. Commits as on 21 October 2014
1922 -----
1923 An experimental POC python implementation that uses Hidden Markov Model for decompression has been committed. But it
1924 -----
1925 (THEORY) 106. Creating a summary graph from EventNet
1926 -----
1927 EventNet graph for historical cause and effect described above can be huge of the order of trillion vertices and edge
1928 events might be necessary at times - similar to a document summarization. Summarizing a graph of event cause-effects
1929 -----
1930 -----
1931 (FEATURE- DONE) 107. Commits as on 1 November 2014
1932 -----
1933 A minimal PAC learning implementation in python to learn a Boolean Conjunction from dataset has been added to reposit
1934 -----
1935 -----
1936 (FEATURE- DONE) 108. Commits as on 4 November 2014
1937 -----
1938 Initial implementation for Minimum Description Length has been added to repository.
1939 -----
1940 -----
1941 (FEATURE- DONE) 109. Commits as on 6 November 2014
1942 -----
1943 Python Shannon Entropy implementation for texts has been added to repository and is invoked in MinimumDescLength.py M
1944 -----
1945 -----
1946 (FEATURE- DONE) 110. Commits as on 7 November 2014
1947 -----
1948 Python Kraft Inequality MDL implementation has been committed.
1949 -----
1950 -----
1951 (FEATURE- DONE) 111. Commits as on 11 November 2014
1952 -----
1953 C++ implementation for Wagner-Fischer Dynamic Programming algorithm that iteratively computes Levenshtein Edit Distar
1954 -----
1955 -----
1956 (FEATURE - DONE) 112. Expirable objects
1957 -----
1958 Setting expiry to an object is sometimes essential to control updates and access to an object. Example application of
1959 should be accessible or displayable for only a finite number of times and after that it has to self-destruct. Though
1960 straightforward with operator overloading, in C it looks non-trivial. Presently only C++ implementation is added to r
1961 -----
1962 -----
1963 (FEATURE- DONE) 113. Commits as on 11 November 2014 - Expirable template class implementation
1964 -----
1965 -----
1966 Similar to weak_ptr and shared_ptr, a generic datatype that wraps any datatype and sets an expiry count to it has bee
1967 in cpp-src/expirable/. For example, a bitmap or a JPEG image can be wrapped in expirable container and it can be acc
1968 If expiry count is 1, the object (an image for example) can be written to or displayed only once and thus a singletor
1969 only for rvalues. Implementing for lvalues (just a usage without assignment should be able to expire an object) seems
1970 there is no operator overloading available for lvalues - i.e there is no "access" operator to overload. This might be
1971 MAC electronic money also.(std::move() copy-by-move instead of a std::swap() copy-by-swap idiom)
1972 -----
1973 -----
1974 (FEATURE- DONE) 114. Commits as on 12 November 2014
1975 -----
1976 Expirable template in asferexpirable.h has been updated with 2 operator=()
1977 functions for copy-assignment and move-assignment which interally invoke
1978 std::swap() and std::move(). Explicit delete(s) are thus removed. Also example
1979 testcase has been updated to use a non-primitive datatype.
1980 -----
1981 -----
1982 (FEATURE- DONE) 115. Commits as on 13 November 2014
1983 -----
1984 Overloaded operator*() function added for expiry of "access" to objects. With this problem mentioned in 113 in tracki
1985 circumvented indirectly.
1986 -----
1987 -----
1988 (FEATURE- DONE) 116. Commits as on 15 November 2014
1989 -----
1990 Python implementation for Perceptron and Gradient has been added to repository.
1991 -----
1992 -----
1993 (FEATURE- DONE) 117. Commits as on 17 November 2014
1994 -----
1995 Python implementation for Linear and Logistic Regression in 2 variables.
1996 -----
1997 -----
1998 (FEATURE- DONE) 118. Commits as on 20 November 2014
1999 -----
2000 C++ implementation of K-Means clustering with edit distance as metric has been added to
2001 repository.

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2002
2003
2004
2005
2006 (FEATURE- DONE) 119. Commits as on 21 November 2014
2007
2008
2009
2010
2011
2012
2013
2014 (FEATURE- DONE) 120. Commits as on 24 November 2014
2015
2016
2017
2018
2019
2020 Python script for decoding encoded horoscope strings (from Maitreya's Dreams) has been added to
2021
2022
2023
2024
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2026
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2034
2035 (THEORY) 121. Commits as on 25 November 2014
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2082
Initial implementation for EventNet:
1. EventNet python script has inputs from two text files - EventNetEdges.txt and EventNetVertices.txt - which define
2. This uses GraphViz (that in turn writes a dot file) and python-graph+gv packages
3. GraphViz writes to EventNet.graphviz.pdf and EventNet.gv.png rendered and visualized graph files.
4. Above text files are disk-stored and can be grown infinitely.
5. EventNetVertices.txt has the format:
<event vertex> - <csv of partakers in the event vertex>
EventNetEdges.txt has the format:
<ordered pairs of vertices for each causation edge>
6. Topological Sorting of EventNet using python-graph algorithms package

(THEORY) 123. EventNet - partakers of events and an application of EventNet to a related problem
Event vertices have partakers of event as defined in 122. Point 84-86 previously defined EventNet as
a fractal graph tensor where each vertex is a graph or partakers. Alternative formulation of this is
where the partakers are just key words or persons in that event. For example, a fictitious story can be translated in
(Event- DONE) 124. Commits as on 4 December 2014
EventNet - a cloudwide event ordering with unique id implementation
EventNet has 2 input files for vertices and edges with partakers and
writes an output file with ordering of the events
Input - EventNetVertices.txt has the format:
<event vertex> - <csv of partakers> - <tuples of conversations amongst the partakers # separated>
partakers could be machine id(s) or IP addresses and thread id(s) and the conversations being the
within each event vertex
Input - EventNetEdges.txt has the format:
<event vertex1, event vertex2>
Output - EventNetOrdering.txt has the format:
<index in chronologically ascending order> - <event id>
EventNet script thus is run in a central node which has the input files above that is
updated by all the nodes in cloud. Outgoing edge from an event vertex has partakers from multiple
events and thus is an outcome of the event. If the input files are split and stored in multiple cloud
nodes, the topological sorts for multiple input files have to be merged to create a single cloudwide
ordering.

(THEORY) 125. Massive EventNet computation
Each conversation of the events needs to create a log message that is sent to the EventNet service
which updates the input vertices and edges files. The python EventNet script run optionally on a hadoop
cluster mapreduce recomputes the topological ordering periodically. This is quite tedious a process that can flood th
(Event- DONE) 126. Commits as on 5 December 2014
Initial C++ Boost::graph based implementation for EventNet has been added to repository.

(THEORY) 127. 2-dimensional random walks for decision making (experimental)
Continued from point 49 above, the psychological process of decision making (in a mental conflict with
two opposing directions) is akin to a game theoretical notion of Nash Equilibrium - where a huge payoff

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2083 matrix is constructed for the random walk directions as strategies for the two conflicting decisions. There could be
2084
2085
2086
2087
2088
2089
2090
2091 128. Commits as on 9 December 2014
2092
2093 Bugfixes for DOT file generation and toposort in C++ EventNet implementation.
2094
2095
2096 129. (THEORY) Draft Updates to https://sites.google.com/site/kuja27/CircuitForComputingErrorProbabilityOfMajorityVot
2097
2098
2099 For even number of finite population (electorate) the binomial coefficient summation in uniform distribution has an  $\epsilon$ 
2100
2101  $(2^n - nC(n/2))/2^{n+1} = 0.5 - \epsilon$  where  $\epsilon = \sqrt{1/(2^n \pi)}$  limit for which vanishes at infinity
2102
2103 (or) probability of good choice is  $\epsilon$  less than 50% for finite even number of electorate for uniform distribution
2104
2105 If this infinite-ness breaches the polynomiality then what is quite puzzling is that RHS becomes a Direct Connect DC
2106
2107 "...
2108 6.6
2109 Circuits of exponential size
2110 As noted, every language has circuits of size  $O(n^{2^n})$ . However, actually finding these circuits may
2111 be difficult000 sometimes even undecidable. If we place a uniformity condition on the circuits, that
2112 is, require them to be efficiently computable then the circuit complexity of some languages could
2113 exceed  $n^{2^n}$ . In fact it is possible to give alternative definitions of some familiar complexity classes,
2114 analogous to the definition of P in Theorem 6.7.
2115 Definition 6.28 (DC-Uniform)
2116 Let  $\{C_n\}_{n \in \mathbb{N}}$  be a circuit family. We say that it is a Direct Connect uniform (DC uniform) family if,
2117 given  $h_n$ ,  $i_i$ , we can compute in polynomial time the  $i$ th bit of (the representation of) the circuit  $C_n$ .
2118 More concretely, we use the adjacency matrix representation and hence a family  $\{C_n\}_{n \in \mathbb{N}}$  is DC
2119 uniform iff the functions SIZE, TYPE and EDGE defined in Remark ?? are computable in polynomial
2120 time.
2121 Note that the circuits may have exponential size, but they have a succinct representation in
2122 terms of a TM which can systematically generate any required node of the circuit in polynomial
2123 time.
2124 Now we give a (yet another) characterization of the class PH, this time as languages computable
2125 by uniform circuit families of bounded depth. We leave it as Exercise 13.
2126
2127 Theorem 6.29
2128 L 000 P H iff L can be computed by a DC uniform circuit family  $\{C_n\}$  that
2129 000 uses AND, OR, NOT gates.
2130  $O(1)$ 
2131 000 has size  $2^n$ 
2132 and constant depth (i.e., depth  $O(1)$ ).
2133 000 gates can have unbounded (exponential) fanin.
2134 000 the NOT gates appear only at the input level.
2135 If we drop the restriction that the circuits have constant depth, then we obtain exactly EXP
2136 ...
2137
2138 The RHS Majority+SAT circuit has all characteristics satisfying the DC-uniformity in the theorem above - size can be
2139
2140 It is not necessary that per voter SAT is same for all voters. Each voter can have unrestricted depth SAT clauses (ir
2141 even if a BQP algorithm is used in voting outside the purview of PH but in EXP, it doesn't change the above unless:
2142 - perfection is impossible i.e there cannot be zero-error processes in the universe
2143 - DC-circuit is not drawable (or undecidable if it can be constructed)
2144 - infinite majority is undecidable (so circuit is DC non-uniform and not DC-uniform)
2145 - the voter CNF can only be 2-SAT (which is highly unlikely) and not k-SAT or 3-SAT
2146
2147
2148 129.1 Toda's theorem and P(good) circuit above:
2149
2150 PH is contained in  $P^{\#P}$  (or)  $P$  with #no-of-solutions-to-SAT oracle (Toda's theorem).
2151 If zero-error Majority+SAT voting DC uniform circuit is in PH then due to LHS=RHS of the P(good) series convergence (
2152 PH collapses?) to P (quite unbelievably):
2153 LHS Pseudorandom choice is in P while RHS Majority+SAT is in PH=DC circuit (restricted depth) or EXP (unrestricted de
2154 (i.e there is a P algorithm for PH).
2155 if P=PH:
2156 P=PH is in  $P^{\#P}$  by Toda's theorem
2157
2158 if P=EXP:
2159 P=PH=EXP in  $P^{\#P}$  or  $P=PH=EXP=P^{\#P}$  (which is a complete collapse)
2160
2161 [p=0.5 is the uniform distribution which is a zero bias space while for other probabilities some bit patterns are les
2162
2163 130. (THEORY) Counterexample definition for P Vs NP
2164
2165 Majority Circuit with SAT voter inputs with finite odd number of voters, in uniform distribution
2166 converges to 1/2 same as LHS for pseudorandom choice. Even number of voters is a special case described

```

2164 previously. Also both LHS and RHS converge to 1 if probability is 1 (without any errors in pseudorandom choice and ma
 2165
 2166
 2167 131. (THEORY) Infinite majority and SAT+Majority Circuit
 2168 -----
 2169 Infinite version of majority circuit is also a kind of heavy hitters problem for streaming algorithms where majority
 2170 -----
 2171 132. (THEORY) May's Theorem of social choice
 2172 -----
 2173 May's Theorem: In a two-candidate election with an odd number of voters, majority rule is the only voting system that
 2174 May's theorem is 2-candidate analog of Arrow's Theorem for 3-candidate condorcet voting. May's theorem for 2 candidat
 2175
 2176 Additional References:
 2177 -----
 2178 132.1 May's theorem - <http://www.math.cornell.edu/~mec/Summer2008/anema/maystheorem.html>
 2179 -----
 2180 133. (THEORY) Pseudorandom number generator and Majority voting for choice on a set
 2181 -----
 2182 Let S be a set of elements with "goodness" attribute for each element. Choice using LHS and RHS on this set is by a F
 2183 133.1 Accuracy of the PRG - how random or k-wise independent the PRG is - this is usually by construction of a PRG (E
 2184 133.2 Goodness of chosen element - PRG is used to choose an element from the set - this mimicks the realworld phenome
 2185 133.3 Thus if the set S is 100% perfect - all elements in it are the best - LHS of P(Good) is 1. Similarly the RHS is
 2186 From the aforementioned, it is evident that for a 100% perfect set, both PRG(LHS) and Majority+SAT(RHS) Voting are two
 2187 -----
 2188 (FEATURE- DONE) 134. Commits as on 8 January 2015
 2189 -----
 2190 134.1 C++ implementation for Longest Common Substring has been added to repository with logs. Datasets were the clust
 2191 134.2 AsFer+USBmd+VIRGO+KingCobra+Acadpdrafts - version 15.1.8 release tagged.
 2192
 2193 -----
 2194 135. (THEORY) Updates, Corrigenda and References to Space Filling Algorithm in :
 2195 <https://sites.google.com/site/kuja27/Analysis%20of%20a%20Randomized%20Space%20Filling%20Algorithm%20and%20its%20Linea>
 2196 -----
 2197 135.1 The standard LP form can be obtained by slack variables (with only equalities) - mentioned as free variables in
 2198
 2199 135.2 Pseudorandom generator with linear stretch in NC1 - <http://homepages.inf.ed.ac.uk/mryan/mfcs01.ps>
 2200 - ... " The notion of deterministically expanding a short seed into a long string that ... the question of whether st
 2201 135.3 This space filling algorithm is in NC (using Tygar-Rief) with an assumption that multiplicative inverse problem
 2202 135.4 Tygar-Rief algorithm outputs n^c bits in parallel (through its PRAM processors) for $n = \log N$ for some composite N
 2203 135.5 Above pseudorandom bits have to be translated into the coordinate positions in the grid which is Z . In other wc
 2204 135.6 Constant c can be suitably chosen as previously to be $c = \log(Z * \log Z) / \log n$ (n need not be equal to Z)
 2205 135.7 Either the n^c sized pseudorandom string can be split sequentially into $(\log Z / 2 + \log Z / 2)$ sized substring coordin
 2206 135.8 In both splits above, same coordinate tuple might get repeated - same bit position can be set to 1 more than or
 2207 135.9 There are Z substrings created out of the 2^{n^c} pseudorandom strings generated by Tygar-Rief Parallel PRG. Henc
 2208 135.10 Maximizing the LP can be reduced to minimizing the collisions (or) repetitive coordinate substrings above thus
 2209 135.11 The grid filling can be formulated as a Cellular Automaton of a different kind - by setting or incrementing th
 2210 135.12 Instead of requiring the non-repetitive coordinate substrings mentioned in (10) supra, the grid filling can be
 2211
 2212 -----
 2213 135.13 Cellular Automaton Algorithm:
 2214 -----
 2215 (Reference for reductions below: <http://cstheory.com/stockmeyer@sbcglobal.net/csv.pdf> [Chandra-Stockmeyer-Vishkin])
 2216 [<http://sourceforge.net/p/asfer/code/HEAD/tree/asfer-docs/AstroInferDesign.txt> and
 2217 <https://github.com/shrinivaasanka/asfer-github-code/blob/master/asfer-docs/AstroInferDesign.txt>]
 2218
 2219 The circuits described in [ChandraStockmeyerVishkin] are constant depth circuits [AC0] and thus in [NC1] (unbounded
 2220
 2221 From wikipedia - Linear programs are problems that can be expressed in canonical form:
 2222 $c^T * X$
 2223 subject to $AX \leq b$
 2224 and $X \geq 0$
 2225
 2226 maximize X
 2227 subject to $AX \leq \text{some maximum limit}$
 2228 and $X \geq 0$

```

2245
2246 Below Cellular Automaton Monte Carlo NC algorithm for grid filling assumes that:
2247 C=[1,1,1,...1]
2248 A=[1,1,1....1] in the above and the vector of variables X is mapped to the grid - sequentially labelled in ascending
2249
2250
2251 Grid cells (or variables in above grid) are initialized to 0.
2252
2253 loop_forever
2254 {
2255     (135.13.1) Parallel Pseudorandom Generator (Tygar-Rief) outputs bit string which are split into coordinates c
2256     (135.13.2) Each grid cell has a constant depth Comparison Circuit that outputs 1 if the grid cell value exceed
2257     (135.13.3) If above Comparison gate outputs 1, then another NC circuit can be constructed that finds the mini
2258 }
2259
2260 Above can be diagrammatically represented as: (for N=a*b cells in grid in parallel)
2261 -----
2262
2263     cell(1,1) ..... cell(a,b)
2264
2265     PRG in parallel .... PRG in parallel
2266     ||                      ||
2267     Comparison .... Comparison
2268     ||                      ||
2269     Minimum of 8 neighbours .... Minimum of 8 neighbours
2270     ||                      ||
2271     Increment .... Increment
2272     and .... and
2273     Decrement .... Decrement
2274
2275 135.14 For example, a 3*3 grid is set by pseudorandom coordinate substrings obtained from Parallel PRG (6,7,7,8,9,1,3
2276
2277     1 1 2
2278     0 0 1
2279     2 1 1
2280
2281 Above can be likened to a scenario where a viscous fluid is unevenly spread at random from heavens.
2282 By applying cellular automaton NC circuit algorithm above, grid becomes: (minimizes collisions,maximizes variables ar
2283
2284     1 1 1
2285     1 1 1
2286     1 1 1
2287
2288 Above can be likened to a scenario where each 8-neighbour grid cell underneath computes the evened-out cellular autom
2289 Thus there are 2 NC + 1 AC circuits which together maximize the special case of P-Complete LP instance without simple
2290
2291
2292 135.15 References on Cellular Automata, Parallel Computation of CA, Fluid Dynamics, Navier-Stokes equation, Percolati
2293
2294 135.15.1 http://www.nt.ntnu.no/users/skoge/prost/proceedings/acc11/data/papers/1503.pdf
2295 135.15.2 http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.52.8377
2296 135.15.3 http://www.stephenwolfram.com/publications/academic/cellular-automaton-fluids-theory.pdf
2297 135.15.4 Constant Depth Circuits - http://www.cs.berkeley.edu/~vazirani/s99cs294/notes/lec5.ps
2298 135.15.5 Complexity Theory Companion - https://books.google.co.in/books?id=ysu-bt4UPPIC&pg=PA281&lpg=PA281&dq=Chandrasekhar+Complexity+Theory+Companion
2299 135.15.6 Pseudorandom Permutation in Parallel - https://www.nada.kth.se/~johanh/onewaync0.ps
2300
2301
2302 135.16 A related algorithm - filling a square with infinitely many inscribed circles
2303
2304 Let S be a square of unit area. This square is filled with infinitely many circles of varying radii. This
2305 can be expressed in terms of geometric equations for circle -  $x(i)^2 + y(i)^2 = r(i)^2$ . Each  $(x(i),y(i))$  is a coordinate
2306
2307 135.17 Above grid can be alternatively formulated as a Voronoi Diagram where Parallel PRG randomly sets multiple point
2308
2309 References:
2310
2311 135.18. Circle Packing and Grid Filling - http://11011110.livejournal.com/332331.html - Filling a square with non-overlapping circles
2312 135.19. 135.16 is a slight variant of Kepler's Theorem [Proof - [Hales] - https://sites.google.com/site/thalespitt/]
2313 135.20 Maximizing Sum of Radii of Balls - [Eppstein] - http://www.ics.uci.edu/~eppstein/pubs/Epp-CCCG-16-slides.pdf
2314 135.21 Thue's Theorem For packing of discs on 2D - http://www.math.stonybrook.edu/~tony/whatsnew/dec00/paper.html - (Feature - Done)
2315
2316
2317 (FEATURE- DONE) 136. Commits as on 28,29 January 2015
2318
2319 Python parser script to translate Longest Common Substring extracted from clustered or classified
2320 set of encoded strings has been added to repository.
2321
2322
2323 (FEATURE - DONE) 137. Mining the Astronomical Datasets using KMeans and kNN - sequence of algorithms in AstroInfer
2324 - Commits as on 4 February 2015
2325

```

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2326 1. MaitreyaToEnchoros.py - This scripts reads a text file with set of date,time and long/lat for a specific class of
2327 2. asfer.cpp is executed with doClustering=true by which KNN and KMeans clustered data are obtained.
2328 3. asferKmeansclustering.cpp and asferKNNclustering.cpp implement the KMeans and kNN respectively.
2329 4. Set of strings from any of the clusters has to be written manually in asfer.enchoros.clustered
2330 5. asferlongestcommonsubstring.cpp - Within each cluster a pairwise longest common substring is found out.
2331 6. TranslateClusterPairwiseLCS.py - Translates the longest common substring to textual rule description mined from at
2332
2333 -----
2334 (FEATURE - DONE) 138. Commandline sequence for Mining Astronomical Datasets (e.g Earthquakes as above)
2335 using KMeans and kNN - Commits as on 4 February 2015
2336 -----
2337 138.1 In asfer.cpp, set doClustering=true and build asfer binary
2338 138.2 Set asfer.enchoros to asfer.enchoros.ascrelative or asfer.enchoros.zodiacal
2339 138.3 $./asfer 2>&1 > logfile1
2340 138.4 From logfile1 get maximum iteration clustered data for any cluster and update asfer.enchoros.clustered
2341 138.5 In asfer.cpp set doLCS=true and build asfer binary
2342 138.6 $./asfer 2>&1 > logfile2
2343 138.7 grep "Longest Common Substring for" logfile2 2>&1 > python-src/asfer.ClusterPairwiseLCS.txt
2344 138.8 sudo python TranslateClusterPairwiseLCS.py | grep "Textually" 2>&1 >> MinedRulesFromDatasets.earthquakes
2345
2346 -----
2347 (FEATURE - DONE) 139. BigData Analytics subsystem (related to point 64,65 on software analytics)
2348
2349 139.1 (DONE) As mentioned in commit notes(13February2015) below, new multipurpose Java Hadoop MapReduce
2350 code has been added to a bigdata_analytics/ directory. At present it computes the frequencies of astronomical entitie
2351
2352 139.2 VIRGO Linux Kernel has following design choices to interface with the machine learning code
2353 in AsFer :
2354     139.2.1 (DONE) the kernel module does an upcall to userspace asfer code - already this facility exists in VIF
2355     139.2.2 (INITIAL VIRGO COMMITS - DONE) the analytics subsystem creates a policy config file /etc/virgo_kernel
2356     139.2.3 (INITIAL ASFER COMMITS - DONE) kernel module implements the machine learning algorithm in C (C++ in k
2357
2358 Diagrams depicting the above options have been uploaded at: http://sourceforge.net/p/asfer/code/HEAD/tree/asfer-docs/
2359
2360 -----
2361 (FEATURE - DONE) Commits as on 4 February 2015
2362 -----
2363 C++ implementation of Knuth-Morris-Pratt String Match Algorithm added to repository.
2364
2365 -----
2366 (FEATURE - DONE) Commits as on 9 February 2015
2367 -----
2368 Python+R script for DFT analysis of multimedia data has been added to repository.
2369
2370 -----
2371 (FEATURE - DONE) Commits as on 13 February 2015
2372 -----
2373 Initial commits for BigData Analytics (for mined astro datasets) using Hadoop 2.6.0 MapReduce:
2374
2375 - new folder bigdata_analytics has been added
2376 - hadoop_mapreduce is subfolder of above
2377 - A Hadoop Java MapReduce implementation to compute frequencies of astronomical entities in MinedRulesFromDatasets.ea
2378 - This jar was executed on a Single Node Hadoop Cluster as per the documentation at:
2379     - http://hadoop.apache.org/docs/stable/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial
2380     - http://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-common/SingleCluster.html
2381 - The HDFS filesystem data is in hdfs_data - /user/root output with frequencies are in userroot_output and namenode a
2382 - hdfs_data also has commandlines history and the console output logs for above.
2383
2384 -----
2385 (FEATURE - DONE) Commits as on 17 February 2015
2386 -----
2387 Python implementations for LogLog and HyperLogLog cardinality estimation for streamed multiset data have been added t
2388
2389 -----
2390 (FEATURE - DONE) Commits as on 18 February 2015
2391 -----
2392 Python implementations for CountMinSketch(frequencies and heavy-hitters) and BloomFilter(membership) for Streaming Da
2393
2394 -----
2395 (FEATURE - DONE) Commits as on 19,20 February 2015
2396 -----
2397 Python clients for Apache Hive and HBase have been added to repository and invoked from
2398 Stream Abstract Generator script as 2-phase streamer for Streaming_<algorithm> scripts.
2399 Hive,Pig,HBase HDFS and script data added to repository in java-src/bigdata_analytics.
2400
2401 -----
2402 (FEATURE - DONE) 140. Schematic for Apache Cassandra/Hive/HBase <=> AsFer Streaming_<algorithm> scripts interface
2403
2404 -----
2405 ($) BigData Source(e.g MovieLens) => Populated in Apache Cassandra, Apache HiveQL CLI(CREATE TABLE..., LOAD DATA LOCA
2406

```

```

2407 ($ Apache Hive or HBase SQL/NoSQL or Cassandra table => Read by Apache Hive or HBase or Cassandra python client => $  

2408  

2409  

2410 (FEATURE - DONE) Commits as on 25 February 2015  

2411 -----  

2412 Added the Hive Storage client code for Streaming Abstract Generator __iter__ overridden function. With this Streaming  

2413  

2414 (DONE) 141. Classpaths required for Pig-to-Hive interface - for pig grunt shell in -x local mode  

2415 -----  

2416 1. SLF4J jars  

2417 2. DataNucleus JDO, core and RDBMS jars (has to be version compatible)  

2418 in pig/lib and hive/lib directories:  

2419 datanucleus-api-jdo-3.2.6.jar  

2420 datanucleus-core-3.2.10.jar  

2421 datanucleus-rdbms-3.2.9.jar  

2422 3. Derby client and server jars  

2423 4. Hive Shims jars  

2424 hive-shims-0.11.0.jar  

2425 5. All Hadoop core jars in /usr/local/hadoop/share/hadoop:  

2426 common hdfs httpfs kms mapreduce tools yarn  

2427 6. HADOOP_CONF_DIR($HADOOP_HOME/etc/hadoop) is also required in classpath.  

2428 -----  

2429 (DONE) 142. Classpaths required for Pig-to-HBase interface  

2430 -----  

2431 In addition to the jars above, following cloudera trace jars are required:  

2432 htrace-core-2.01.jar and htrace-1.45.jar  

2433  

2434 hadoop2_core_classpath.sh shell script in bigdata_analytics exports all the jars in (141) and (142).  

2435  

2436 (FEATURE - DONE) Commits as on 26 February 2015  

2437 -----  

2438 Pig-HBase stream_data table creation and population related Pig scripts, HDFS data and screenshots have been added to  

2439  

2440 (FEATURE - DONE) Commits as on 27 February 2015  

2441 -----  

2442 Cassandra Python Client has been added to repository and Streaming_AbstractGenerator.py has been  

2443 updated to invoke Cassandra in addition to Hive,HBase and File storage. Cassandra data have been added  

2444 in bigdata_analytics/  

2445  

2446 143. (FEATURE - DONE) Storage Abstraction in AsFer - Architecture Diagram  

2447 -----  

2448 Architecture diagram for Hive/Cassandra/HBase/File NoSQL and other storage abstraction implemented in python has been  

2449  

2450 144. (FEATURE - DONE) Apache Spark and VIRGO Linux Kernel Analytics and Commits as on 6 March 2015  

2451 -----  

2452 1. Prerequisite: Spark built with Hadoop 2.6.0 with maven commandline:  

2453 mvn -Pyarn -Phadoop-2.4 -Dhadoop.version=2.6.0 -DskipTests package  

2454  

2455 2. Spark Python RDD MapReduce Transformation script for parsing the most frequent source IP address  

2456 from Uncomplicated FireWall logs in /var/log/kern.log has been added to repository. This parsed  

2457 IP address can be set as a config in VIRGO kernel_analytics module (/etc/virgo_kernel_analytics.conf)  

2458  

2459 (FEATURE - DONE) Commits as on 10 March 2015  

2460 -----  

2461 Spark python script updated for parsing /var/log/udev and logs in python-src/testlogs.  

2462 (spark-submit Commandline: bin/spark-submit /media/shrinivasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea22/home/kashrini  

2463  

2464 145. (FEATURE - DONE) Commits as on 26 March 2015  

2465 -----  

2466 New python script to fetch stock quotes by ticker symbol that can be used for Streaming_<algorithm> scripts has been  

2467  

2468 146. (FEATURE - DONE) Commits as on 2 April 2015  

2469 -----  

2470 New Python script to get Twitter tweets stream data for a search query has been added.  

2471  

2472 147. (FEATURE - DONE) Related to Item 3 - Sequence Mining Implementation - Commits as on 3 April 2015  

2473 -----  

2474 Python class that implements Apriori GSP algorithm for mining frequent subsequences in ordered sequences  

2475 dataset has been added to repository. Though exponential, together with Longest Common Subsequence, Apriori GSP gives  

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2488 148. An example Class Association Rule Learnt from Sequence Mining:
2489 -----
2490 For length 6 most frequent subsequences in earthquake astronomical data from 1900 are: ('conjoinedplanets',frequency)
2491 -----
2492 [('0', 313), ('4', 313), ('8', 313), ('3', 313), ('7', 313), ('2', 313), ('6', 313), ('1', 313), ('5', 313), ('9', 31
2493 -----
2494 indices for planets:
2495 -----
2496 * 0 - for unoccupied
2497 * 1 - Sun
2498 * 2 - Moon
2499 * 3 - Mars
2500 * 4 - Mercury
2501 * 5 - Jupiter
2502 * 6 - Venus
2503 * 7 - Saturn
2504 * 8 - Rahu
2505 * 9 - Ketu
2506
2507 Some inferences can be made from above:
2508 -----
2509 By choosing the creamy layer of items with support > 30 (out of 313 historic events) - ~10%:
2510 [('14', 121), ('46', 66), ('56', 51), ('13', 51), ('34', 42), ('45', 36), ('9a', 33), ('79', 31), ('24', 30), ('16',
2511
2512 Above implies that:
2513 -----
2514 Earthquakes occur most likely when, following happen - in descending order of frequencies:
2515 - Sun+Mercury (very common)
2516 - Mercury+Venus
2517 - Jupiter+Venus
2518 - Sun+Mars
2519 - Mars+Mercury
2520 - Mercury+Jupiter
2521 - Ketu is in Ascendant
2522 - Saturn+Ketu
2523 - Moon+Mercury
2524 - Sun+Venus
2525
2526 Machine Learnt pattern above strikingly coincides with some combinations in Brihat Samhita (Role of Mars, Nodes, and
2527
2528 Some recent major intensity earthquakes having above sequence mined astronomical conjunctions :
2529 -----
2530 Sendai Earthquake - 11 March 2011 14:46 - Sun+Mars in Aquarius, Mercury+Jupiter in Pisces
2531 Nepal Earthquake - 25 April 2015 11:56 - Sun+Mars+Mercury in Aries
2532 Chile Earthquake - 16 September 2015 22:55 - Sun+Mars+Jupiter in Leo
2533 All three have Sun+Mars coincidentally.
2534
2535
2536 -----
2537 (FEATURE - DONE) Commits as on 5 April 2015
2538 -----
2539 Textual translation of Class Association Rules added to SequenceMining.py with logs.
2540
2541 -----
2542 (FEATURE - DONE) Commits as on 13 April 2015
2543 -----
2544 Python implementation of :
2545 - Part-of-Speech tagging using Maximum Entropy Equation of Conditional Random Fields(CRF) and
2546 - Viterbi path computation in HMM-CRF for Named Entity Recognition has been added to repository.
2547
2548
2549 -----
2550 (FEATURE - DONE) Commits as on 15 April 2015
2551 -----
2552 Named Entity Recognition Python script updated with:
2553 - More PoS tags
2554 - Expanded HMM Viterbi probabilities matrix
2555 - Feature function with conditional probabilities on previously labelled word
2556
2557 -----
2558 (FEATURE - DONE) Commits as on 17 April 2015
2559 -----
2560 Twitter Streaming python script updated with GetStreamFilter() generator object for streaming tweets data.
2561
2562 -----
2563 (FEATURE - DONE) 149. Commits as on 10 May 2015
2564 -----
2565 A Graph Search NetworkX+MatPlotLib Visualizer for WordNet has been implemented in python and has been added to reposi
2566
2567 -----
2568 (FEATURE - DONE) Commits as on 12 May 2015

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2569
2570 WordNet Visualizer script has been updated to take and render the WordNet subgraph computed by Recursive Gloss Overla
2571 - http://arxiv.org/abs/1006.4458
2572 - http://www.nist.gov/tac/publications/2010/participant.papers/CMI\_IIT.proceedings.pdf
2573 - https://sites.google.com/site/kuja27/PresentationTAC2010.pdf?attredirects=0
2574
2575
2576 (FEATURE - DONE) 150. Commits as on 14 May 2015
2577
2578 Updated WordNet Visualizer with:
2579 - bidirectional edges
2580 - graph datastructure changed to dictionary mapping a node to a list of nodes (multigraph)
2581 - With these the connectivity has increased manifold as shown by gloss overlap
2582 - the graph nodes are simply words or first element of lemma names of the synset
2583 - more networkx drawing layout options have been added
2584
2585 Added code for:
2586 - removing self-loops in the WordNet subgraph
2587 - for computing core number of each node (maximum k such that node is part of k-core decomposition)
2588
2589 In the input example, nodes "India" and "China" have core numbers 15 and 13 respectively which readily classify the c
2590 class "India and China". Thus a new unsupervised classifier is obtained based on node degrees.
2591
2592
2593 (FEATURE - DONE) Commits as on 16 May 2015
2594
2595 - added sorting the core numbers descending and printing the top 10% core numbers which are prospective classes the c
2596 This is a new unsupervised text classification algorithm and is based on recursive gloss overlap algorithm in http://www.nist.gov/tac/publications/2010/participant.papers/CMI\_IIT.proceedings.pdf. A major feature of this algorit
2597
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2600 (FEATURE - DONE) 151. Commits as on 18 May 2015
2601
2602 An interesting research was done on the wordnet subgraph obtained by Recursive Gloss Overlap algorithm:
2603 - PageRank computation for the WordNet subgraph was added from NetworkX library. This is probably one of the first ap
2604 a graph other than web link graph.
2605 - The objective was to find the most popular word in the subgraph obtained by the Random Walk Markov Model till it st
2606 - The resultant word with maximum pagerank remarkably coincides with the most probable class of the document and is a
2607 ranking to core numbers of nodes ranked descending.
2608 - Some random blog text was used.
2609 - Above was mentioned as a theoretical statement in 5.12 of http://www.nist.gov/tac/publications/2010/participant.pap
2610
2611
2612 (FEATURE - DONE) Commits as on 19 May 2015
2613
2614 A primitive text generation from the definition graph has been implemented by:
2615 - computing the k-core of the graph above certain degree k so that the core is dense
2616 - each edge is mapped to a relation - at present "has" , "is in" are the only 2 relations (more could be added based
2617 hypernyms)
2618 - Each edge is output as "X <relation> Y"
2619 - Above gives a nucleus text extracted from the original document
2620 - It implements the theory mentioned in: https://sites.google.com/site/kuja27/DocumentSummarization\_using\_SpectralGra
2621
2622
2623 (FEATURE - DONE) Commits as on 20 May 2015
2624
2625 Hypernyms/Hyponyms based sentence construction added to WordNet Visualizer. The core-number and pagerank based classi
2626
2627
2628 (FEATURE - DONE) Commits as on 21 May 2015
2629
2630 Updated the Visualizer to print the WordNet closure of hypernyms and hyponyms to generate a blown-up huge sentence. T
2631 uncovers new vertices and edges in the definition graph (strict supergraph of RGO graph) and it is a mathematically g
2632 (similar to first order logic and functional programming compositionality) and mimicks an ideal human-thinking proces
2633
2634
2635 (FEATURE - DONE) 151. Commits as on 22,23,24 May 2015
2636
2637 Added code for computing recursive composition of lambda functions over the RGO graph relations(edges):
2638 - For this the Depth First Search Tree of the graph is computed with NetworkX
2639 - The lambda function is created for each edge
2640 - Composition is done by concatenating a recursive parenthesisation string of lambda expressions:
2641     for each DFS edge:
2642         Composed_at_tplus1 = Composed_at_t(lambda <edge>)
2643 - DFS is chosen as it mimicks a function invocation stack
2644 - Lambda composition closure on the Recursive Gloss Overlap graph has been rewritten to create a huge lambda composit
2645 not exist in WordNet parlance, because the Recursive Gloss Overlap algorithm grows a graph recursively from WordNet S
2646 - Thus a tree is built which is made into a graph by pruning duplicate edges and word vertices. WordNet graph does nc
2647 - Thus RGO in a way adds new hierarchical recursive relationships to WordNet based on Synset definition.
2648 - The lambda composition obtained above is a mathematical or lambda calculus representation of a text document - Natu
2649

```

```

2650 -----
2651 (FEATURE - DONE) Commits as on 26 May 2015
2652 -----
2653 Added initial code for Social Network Analyzer for Twitter following to create a NetworkX graph and render it with Ma
2654 -----
2655 (FEATURE - DONE) Commits as on 3 June 2015
2656 -----
2657 Bonacich Power Centrality computation added to Twitter Social Network Analyzer using PageRank computation.
2658 -----
2659 -----
2660 (FEATURE - DONE) Commits as on 4 June 2015
2661 -----
2662 - Eigen Vector Centrality added to Twitter Social Network Analyzer.
2663 - File storage read replaced with Streaming_AbstractGenerator in Streaming_HyperLogLogCounter.py and Streaming_LogLog
2664 -----
2665 -----
2666 (FEATURE - DONE) 152. Commits as on 7 June 2015
2667 -----
2668 New Sentiment Analyzer script has been added to repository:
2669 - This script adds to WordNet Visualizer with Sentiment analysis using SentiWordNet from NLTK corpus
2670 - added a Simple Sentiment Analysis function that tokenizes the text and sums up positivity and negativity score
2671 - A non-trivial Sentiment Analysis based on Recursive Gloss Overlap graph - selects top vertices with high core numbe
2672 and elicits the positivity and negativity of those vertex words.
2673 - Above is intuitive as cores of the graph are nuclei centering the document and the sentiments of the vertices of th
2674 are important which decide the sentiment of the whole document.
2675 - Analogy: Document is akin to an atom and the Recursive Gloss Overlap does a nuclear fission to extricate the inner
2676 (subatomic particles are the vertices and forces are edges)
2677 - Instead of core numbers, page_rank can also be applied (It is intriguing to see that classes obtained from core_num
2678 and page_rank coincide to large extent) and it is not unusual to classify a document in more than one class (as it is
2679
2680 Above script can be used for any text including social media and can be invoked as a utility from SocialNetworkAnalys
2681 Microblogging tweets are more crisp and "emotionally precise" i.e. extempore - convey instantaneous sentiment (withou
2682
2683 -----
2684 (FEATURE - DONE) Commits as on 8 June 2015
2685 -----
2686 Commits for:
2687 - fixing errors due to NLTK API changes in lemma_names(), definition() ... [ variables made into function calls ]
2688 - Unicode errors
2689 - Above were probably either due to Ubuntu upgrade to 15.04 which might have added some unicode dependencies and/or
2690 (SentimentAnalyzer.py already has been updated to reflect above)
2691
2692 -----
2693 (FEATURE - DONE) Commits as on 10 June 2015
2694 -----
2695 Sentiment Analysis for twitter followers' tweets texts added to SocialNetworkAnalysis_Twitter.py which invokes Sentim
2696
2697 -----
2698 (FEATURE - DONE) Commits as on 13 June 2015
2699 -----
2700 Sentiment Analysis for tweet stream texts added to SocialNetworksAnalysis_Twitter.py which invokes SentimentAnalyzer.
2701
2702 -----
2703 153. (FEATURE - THEORY - Minimum Implementation DONE) Sentiment Analysis as lambda function composition of the Recur
2704 -----
2705 SentiWordNet based scoring of the tweets and texts have some false positives and negatives. But the lambda compositio
2706 Recursive Gloss Overlap graph is done by depth-first-search - set of composition trees which overlap. If each edge is
2707 a function of sentiment scores of two vertex words, then lambda composition performed over the graph is a better repr
2708 of the document. This is at present a conjecture only. An implementation of this has been added to SentimentAnalyzer.
2709 Propagation of a sentiment potential in the Recursive Gloss Overlap graph considering it as a Bayesian graphical mode
2710
2711 -----
2712 Commits as on 15 June 2015
2713 -----
2714 NeuronRain - (AsFer+USBmd+VIRGO+KingCobra) - version 15.6.15 release tagged
2715 Most of features and bugfixes are in AsFer and VIRGO
2716
2717 -----
2718 154. (FEATURE - DONE) Belief Propagation and RGO - Commits as on 20 June 2015
2719 -----
2720 SentimentAnalyzer is updated with a belief propagation algorithm (Pearl) based Sentiment scoring by
2721 considering Recursive Gloss Overlap Definition Graph as graphical model and sentiwordnet score for
2722 edge vertices as the belief potential propagated in the bayesian network (RGO graph). Since the
2723 sentiment is a collective belief extracted from a text rather than on isolated words and the
2724 sentiwordnet scores are probabilities if normalized, Sentiment Analysis is reduced to Belief Propagation problem.
2725 The previous Belief Propagation function is invoked from SocialNetworkAnalysis_-> code to Sentiment Analyze tweet str
2726
2727 -----
2728 155. Updates to https://sites.google.com/site/kuja27/DocumentSummarization_using_SpectralGraphTheory_RGOGraph_2014.pc
2729
2730

```

2731
 2732 Algorithms and features based on Recursive Gloss Overlap graph:
 2733 155.1 RGO visualizer
 2734 155.2 RGO based Sentiment Analyzer - Belief Propagation in RGO as a graphical model
 2735 155.3 Graph Search in text - map a text to wordnet relations by RGO graph growth - prints the graph edges which are r
 2736 a text
 2737 155.4 New unsupervised text classifier based in RGO core numbers and PageRank
 2738 155.5 Social Network Analyzer (Tweets analysis by RGO graph growth)
 2739 155.5 Lambda expression construction from the RGO graph
 2740 155.6 Sentence construction by composition of edges
 2741
 2742
 2743 156. (FEATURE - DONE) Commits as on 4 July 2015 - RGO sentiment analyzer on cynical tweets
 2744
 2745 Added query for a "elections" to stream tweets related to it. Few sample cynical tweets were sentiment-analyzed with
 2746 RGO Belief Propagation SentimentAnalyzer that gives negative sentiment scores as expected whereas trivial SentiWordNet
 2747 gives a positive score wrongly.
 2748
 2749
 2750 157. (THEORY) Recursive Gloss Overlap graphical model as a Deep Learning algorithm that is an alternative to Perceptr
 2751
 2752 Point 155 mentions the diverse applications of Recursive Gloss Overlap algorithm each of which touch upon multiple fa
 2753
 2754
 2755 158. (THEORY) Graph Discovery (or) Graph Guessing and EventNet (related to EventNet points 70-79)
 2756
 2757 EventNet mentioned previously is an infinite cause-effect graph of event vertices with partakers for each event
 2758 (kind of a PetriNet yet different). A special case of interest is when only few subgraphs of a giant EventNet is avai
 2759 often necessary to discover or guess the complete graph of causality with partakers. A familiar example is a crime sc
 2760 where:
 - it is necessary to recreate the complete set of events and their causalities with partakers of a crime (reverse-er
 - but only few clues or none are available - which are akin to very sparse subgraphs of the crime scene EventNet
 - Guessing (100-x)% of the graph from x% clue subgraphs can be conjectured to be an NP problem - because non-determi
 EventNet path can be guessed. As a counting problem this is *#P-complete* (set of all paths among known subgraphs of ar
 2761
 2762
 2763
 2764
 2765
 2766 Another example: set of blind men try to make out an object by touch.
 2767
 2768
 2769 159. (THEORY) Pattern Grammar and Topological Homeomorphism of Writing Deformations
 2770
 2771 Grammar for patterns like texts, pictures similar to RE,CFG etc., for pattern recognition:
 2772 - example text grammar: <a> := <o> <operator> </>
 2773 - example text grammar: <d> := <o> <operator> <l>
 2774 - example text grammar: <v> := <\> <operator> </>
 2775 Previous grammar is extensible to any topological shapes. For example, handwriting of 2 individuals are
 2776 homeomorphic deformations.
 2777
 2778 References:
 2779
 2780 159.1 Topology and Graphics - <https://books.google.co.in/books?id=vCc8DQAAQBAJ&pg=PA263&lpg=PA263&dq=homeomorphism+ar>
 2781
 2782
 2783 160. (THEORY) Cognitive Element
 2784
 2785 An element of a list or group is cognitive with respect to an operator if it "knows" about all or subset of other ele
 2786 - In list 2,3,5,7,17 - 17 knows about 2,3,5,7 in the sense that $17 = 2+3+5+7$ with + operator
 2787 - In list "addon", "add", "on" - "addon" knows about "add" and "on" with concatenation operator
 2788 - In list "2,3,6,8,9,10,..." - 6 knows about 2 and 3, 10 knows about 2 and 5 with factorization as operator.
 2789 This might have an equivalent notion in algebra. Motivation for this is to abstract cognition as group operator. Esse
 2790 to an equivalence relation graph where elements are related by a cognitive operator edge.
 2791
 2792
 2793
 2794 161. (THEORY) Philosophical intuition for P(Good) summation - Continuation of (129) and other previous related points
 2795
 2796 The apparent paradox in Perfect Voting can be reconciled as below to some extent:
 2797 - Voting is done in parallel in real-world elections and not serially
 2798 - Votes are counted in parallel - iterated integer addition in NC1 (<http://www.ccs.neu.edu/home/viola/classes/gems-06>)
 2799 - Thus if RHS is just Circuit-Value Problem and not a Circuit-SAT then LHS getting equated to RHS is not unusual - bc
 2800 - Separation of RHS from LHS happens only when the Circuit-SAT is required in RHS.
 2801 - P(Good) convergence in perfect voting implies that Voter SAT is not necessary if there is perfection (proving the c
 2802 true even though the PRG is imperfect that operates to choose on a perfect set.
 2803 - Parallelism implies NC circuits
 2804 - Above applies to infinite majority also (Mark Fey)
 2805 - RHS in worst-case can be EXP-Complete if the Majority+Voter SAT oracle circuit is of unrestricted depth and lot of
 2806
 2807
 2808 162. (THEORY) Majority Voting Circuit with Boolean Function Oracles
 2809
 2810 If each voter has a boolean function to decide which has fanout > 1 gates instead of a formula, RHS Majority Voting t
 2811 Decision tree, Certificate, and other complexity measures automatically come into reckoning. Thus RHS circuit is an

```

2812
2813 References:
2814 -----
2815 162.1 http://www.cs.cmu.edu/~odonnell/papers/barbados-aobf-lecture-notes.pdf
2816 162.1 http://www.math.u-szeged.hu/~hajnal/research/papers/dec\_surv.gz
2817
2818 -----
2819 163. (THEORY) Parity and Constant Depth - intuition (not a formal proof, might have errors)
2820 -----
2821 Inductive Hypothesis:
2822 -----
2823 For depth d and n variables parity has  $n^k$  sized circuit.
2824
2825 For n+1 variables:
2826 -----
2827     XOR gate
2828     /   \
2829 n-variable   (n+1)th variable
2830 circuit
2831
2832 Each XOR gate is of atleast depth 2 or 3 with formula -  $(x \wedge \neg y) \vee (\neg x \wedge y)$ . Thus for each additional variabl
2833
2834 -----
2835 164. (FEATURE - DONE) Commits as on 16 September 2015
2836 -----
2837 cpp-src/cloud_move - Implementation of Move Semantics for Cloud objects:
2838 -----
2839 This expands on the usual move semantics in C++ and implements a Perfect Forwarding of objects over cloud. A move cli
2840
2841 VIRGO kernel sockets code has been carried over and changed for userspace that uses traditional sockaddr_in and htons
2842
2843 C++ sockets reference code adapted for std::move - for use_addrinfo clause:
2844 - getaddrinfo linux man pages
2845 - http://codebase.eu/tutorial/linux-socket-programming-c/ (addrinfo instead of usual sockaddr_in and htons)
2846
2847 Move semantics schematic:
2848 -----
2849     &
2850     member fn temp arg lvalue <-----source data rvalue
2851     |           /
2852     & |           / && (removes a temp copy)
2853     |           /
2854     V           /
2855 client proxy destination lvalue<-/
2856     |
2857     |-----> cloud server destination
2858
2859 lvalue reference& does additional copy which is removed by rvalue reference&& to get the rvalue directly. Move client
2860
2861 -----
2862 165. (FEATURE - DONE) Commits as on 18 September 2015
2863 -----
2864 Cloud Perfect Forwarding - Google Protocol Buffer Currency :
2865
2866 Currency object has been implemented with Google Protocol Buffers - in cloud_move/protocol_buffers/ src_dir and out_c
2867 - lack of JSON format language specific compilers
2868 - XML is too complicated
2869 - Protocol Buffers also have object serialization-to-text member functions in generated C++ classes.
2870
2871 Protocol Buffer compilation after change to currency object:
2872 protoc -I=src_dir/ --cpp_out=out_dir/ src_dir/currency.proto
2873
2874 -----
2875 166. (THEORY) Related to 65 - Debug Analytics (as part of Software Analytics)
2876 -----
2877 Debugging software is painful process with repetitive labour - For example kernel and device driver development has t
2878 1. Writing the kernel patch code for some deep kernel panics.
2879 2. Kernel incremental or full build.
2880 3. Test the patch.
2881 (1),(2) and (3) are sometimes frustratingly repetitive. If the debugging is represented as a state machine automaton,
2882
2883 References:
2884 166.1 Learning Finite State Machines - https://www.cs.upc.edu/~bballe/other/phdthesis.pdf
2885
2886 -----
2887 167. (THEORY) Prestige based ranking and Condorcet Elections
2888 -----
2889 Web Search Engine Rankings by prestige measures are n-tuples of rankings (for n candidate web pages where n could be
2890
2891 -----
2892 168. (FEATURE - DONE) Commits as on 20,21,22 October 2015

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```

2893 -----
2894 Initial code for LinkedIn crawl-scrape. Uses Python-linkedin from https://github.com/ozgur/python-linkedin with
2895 some additional parsing for url rewriting and wait for authurl input:
2896 - prints a linkedin url which is manually accessed through curl or browser
2897 - created redirect_url with code is supplied to raw_input "authurl:"
2898 - parses the authcode and logs-in to linkedin to retrieve profile data; get_connections() creates a forbidden error
2899
2900 Logs for the above has been added to testlogs
2901
2902 -----
2903 169. (FEATURE - DONE) Commits as on 28 October 2015
2904 -----
2905 Deep Learning Convolution Perceptron Python Implementation.
2906
2907 -----
2908 170. (FEATURE - DONE) Commits as on 29 October 2015, 1 November 2015
2909 -----
2910 Deep Learning BackPropagation Multilayered Perceptron Python Implementation.
2911
2912 -----
2913 171. Commits as on 3 November 2015
2914 -----
2915 DeepLearning BackPropagation implementation revamped with some hardcoded data removal.
2916
2917 -----
2918 172. (FEATURE - DONE) Hurricane Datasets Sequence Mining - Commits as on 4 November 2015
2919 -----
2920 Miscellaneous code changes:
2921 -----
2922 - Weight updates in each iteration are printed in DeepLearning_BackPropagation.py
2923 - Changed maitreya_textclient path for Maitreya's Dreams 7.0 text client; Updated to read HURDAT2 NOAA Hurricane Data
2924 - Maximum sequence length set to 7 for mining HURDAT2 asfer.enchoros.seqmining
2925 - New files asfer.enchoros.ascrelative.hurricanes, asfer.enchoros.zodiacal.hurricanes have been added which are creat
2926 - an example chartsummary for Maitreya's Dreams 7.0 has been updated
2927 - 2 logs for SequenceMining for HURDAT2 encoded datasets and Text Class Association Rules learnt by SequenceMining.py
2928 - Increased number of iterations in BackPropagation to 100000; logs for this with weights printed are added in testlc
2929
2930 =====
2931 Sorted Candidate support for all subsequence lengths - gives an approximate pattern in dataset:
2932 [('0', 1333), ('4', 1333), ('8', 1333), ('3', 1333), ('7', 1333), ('2', 1333), ('6', 1333), ('1', 1333), ('5', 1333),
2933 size of dataset = 1333
2934
2935 =====
2936 Sun , Mercury ,
2937 =====
2938 Class Association Rule 12 mined from dataset: with frequencies: 23.6309077269 percentage
2939 =====
2940 Mercury , Venus ,
2941 =====
2942 Class Association Rule 13 mined from dataset: with frequencies: 19.5798949737 percentage
2943 =====
2944 Venus , Saturn ,
2945 =====
2946 Class Association Rule 14 mined from dataset: with frequencies: 14.2535633908 percentage
2947 =====
2948 Saturn , Rahu ,
2949 =====
2950 Class Association Rule 15 mined from dataset: with frequencies: 14.1785446362 percentage
2951 =====
2952 Jupiter , Ketu ,
2953 =====
2954 Class Association Rule 16 mined from dataset: with frequencies: 13.9534883721 percentage
2955 =====
2956 Mercury , Ketu ,
2957 =====
2958 Class Association Rule 17 mined from dataset: with frequencies: 13.503375844 percentage
2959 =====
2960 Mars , Mercury ,
2961 =====
2962 Class Association Rule 18 mined from dataset: with frequencies: 12.3780945236 percentage
2963 =====
2964 Jupiter , Saturn ,
2965 =====
2966 Class Association Rule 19 mined from dataset: with frequencies: 12.0780195049 percentage
2967 =====
2968 Mercury , Jupiter ,
2969 =====
2970 Class Association Rule 20 mined from dataset: with frequencies: 11.9279819955 percentage
2971 =====
2972 Sun , Mars ,
2973 =====

```

```

2974 Class Association Rule 21 mined from dataset: with frequencies: 11.8529632408 percentage
2975 =====
2976 Jupiter , Venus ,
2977 =====
2978 Class Association Rule 22 mined from dataset: with frequencies: 11.0277569392 percentage
2979 =====
2980 Jupiter , Rahu ,
2981 =====
2982 Class Association Rule 23 mined from dataset: with frequencies: 10.0525131283 percentage
2983 =====
2984 Sun , Moon ,
2985 =====
2986 Class Association Rule 24 mined from dataset: with frequencies: 9.60240060015 percentage
2987 =====
2988 Moon , Mars ,
2989 =====
2990 Class Association Rule 25 mined from dataset: with frequencies: 8.70217554389 percentage
2991 =====
2992 Sun , Mercury , Venus ,
2993 =====
2994 Class Association Rule 26 mined from dataset: with frequencies: 8.6271567892 percentage
2995 =====
2996 Mars , Venus ,
2997 =====
2998 Class Association Rule 27 mined from dataset: with frequencies: 8.47711927982 percentage
2999 =====
3000 Rahu , Ascendant ,
3001 =====
3002 Class Association Rule 28 mined from dataset: with frequencies: 8.10202550638 percentage
3003 =====
3004 Moon , Jupiter ,
3005 =====
3006 Class Association Rule 29 mined from dataset: with frequencies: 7.951987997 percentage
3007 =====
3008 Ketu , Ascendant ,
3009 =====
3010 Class Association Rule 30 mined from dataset: with frequencies: 7.72693173293 percentage
3011 =====
3012 Mars , Mercury , Venus ,
3013 =====
3014
3015 Above are excerpts from the logs added to testlogs/ for Sequence mined from HURDAT2 dataset for hurricanes from 1851
3016
3017 =====
3018 173. (FEATURE - DONE) BigData Storage Backend Abstraction subsystem for AsFer - Commits as on 5 November 2015 :
3019 -----
3020 - These are initial minimal commits for abstracting storage of ingested bigdata for AsFer Machine Learning code
3021 - A dependency injection implementation of database-provider-specific objects is added to repository.
3022 - Presently MySQLdb based MySQL backend has been implemented with decoupled configuration which are injected into Abs
3023
3024 Schematic Dependency Injected Object Graph:
3025 -----
3026             Injector =====
3027             |
3028             |
3029             MySQL_Configuration --- injects config ----> MySQL_DBBackend ---- injects connection ----> Abstract_DE
3030             |
3031             |
3032             |
3033             xxx_Configuration --- injects config ----> xxx_DBBackend ---- injects connection -----|
3034
3035 -----
3036 174. (FEATURE - DONE) AsFer C++ - Python Integration - Embedding Python in AsFer C++ - Commits as on 11 November 2015
3037 -----
3038 Python Embedding in C++ implementation has been added and invoked from asfer main entrypoint with a boolean flag. Thi
3039
3040 Schematic Diagram:
3041 -----
3042             AsFer C++ -----> C Python Embedding -----> AsFer Python -----> Machine Learning algorithms on Spark RDD
3043             / \
3044             |
3045             -----<----- userspace upcall ----->----- VIRGO kernel analytics and other kernel modul
3046
3047 -----
3048 175. (FEATURE - DONE) Config File Support for AsFer C++ and Python Machine Learning Algorithms - Commits as on 12 Nov
3049 -----
3050 Config File support for asfer has been added. In asfer.cpp main(), read_asfer_config() is invoked which reads config
3051
3052 -----
3053 176. (THEORY) Isomorphism of two Document Definition Graphs
3054

```

3055 http://arxiv.org/abs/1006.4458 and http://www.nist.gov/tac/publications/2010/participant.papers/CMI_IIT.proceedings.pdf
 3056
 3057
 3058 177. Commits as on 13 November 2015
 3059
 3060 - Corrections to Convolution Map Neuron computation with per-coordinate weight added
 3061 - Removed hardcoded convolution stride and pooling width in the class
 3062 - testlogs following input bitmap features have been added with the output of 5 neurons in final layer:
 3063 - Without Zero inscribed
 3064 - With Zero inscribed in bitmap as 1s
 3065 - With Bigger Zero inscribed in bitmap as 1s
 3066 - With Biggest Zero inscribed in bitmap as 1s
 3067 The variation of final neural outputs can be gleaned as the size of the pattern increases from none to biggest.
 3068 The threshold has to be set to neural output without patterns. Anything above it shows a pattern.
 3069 - Added a config variable for invoking cloud perfect forwarding binaries in KingCobra in asfer.conf
 3070 - config_map updated in asfer.cpp for enableCloudPerfectForwarding config variable
 3071
 3072
 3073 178. (THEORY) Approximate Machine Translation with Recursive Gloss Overlap Definition Graph
 3074
 3075 For natural language X (=English) an RGO graph can be constructed (based on algorithms in http://arxiv.org/abs/1006.4458)
 3076
 3077
 3078 179. (FEATURE - DONE) Web Spider Implementation with Scrapy Framework - Commits as on 16 November 2015
 3079
 3080 Initial commits for a Web Spider - Crawl and Scrape - done with Scrapy framework. Presently it crawls Google News for
 3081 crawled items in items.py
 3082
 3083
 3084 180. (FEATURE - DONE) Sentiment Analyzer Implementation for Spidered Texts - Commits as on 16 November 2015
 3085
 3086 Sentiment Analyzer implementation for Crawled-Scraped Google News Search result texts with testlogs and screenshots c
 3087 been added. This has been made a specialized analyzer for spidered texts different from twitter analyzer.
 3088
 3089
 3090 181. Commits as on 17 November 2015
 3091
 3092 Requirements.txt for package dependencies have been added to asfer-docs/.
 3093 WebSpider Crawl-Scraped URLs descriptions are inserted into MySQL table (asfer_webspider) by importing backend/Abstra
 3094 implementation. Logs for this Scrapy crawl has been added to webspider/testlogs. WebSpider.py parse() has been update
 3095
 3096
 3097 182. Commits as on 19 November 2015
 3098
 3099 - Added more stop words in spidered text and commented text generation in SocialNetworkAnalysis_WebSpider.py
 3100 - logs and screenshots for this has been added to testlogs/
 3101 - crawl urls in WebSpider.py has been updated
 3102 - Added more edges in definition graph by enumerating all the lemma names of a keyword in previous iteration. This ma
 3103 and probability of a node having more k-core number increases and classification is more accurate.
 3104 - logs and screenshots for updated web spidered news texts of two topics "Theoretical Computer Science" and "Chennai"
 3105
 3106
 3107 183. Commits as on 20 November 2015
 3108
 3109 - Updated Spidered text for Sentiment Analysis
 3110 - Changed the Sentiment Analysis scoring belief potential propagation algorithm:
 3111 - Two ways of scoring have been added - one is based on DFS tree of k-core subgraph of the larger wordnet subgraph
 3112 - Sentiment thus is computed only for the core of the graph which is more relevant to the crux or class of the docu
 3113 vertices are ignored.
 3114 - the fraction score is multiplied by a heuristic factor to circumvent floating points
 3115
 3116
 3117 184. Commits as on 23 November 2015
 3118
 3119 - Updated SentimentAnalyzer.py and SocialNetworkAnalysis_Twitter.py scripts with core number and k-core DFS belief pc
 3120 similar to SocialNetworkAnalysis_WebSpider.py.
 3121 - logs and screenshots for twitter followers graph and tweet RGO graph Sentiment Analysis have been added.
 3122 - Example tweet is correctly automatically classified into "Education" class based on top core number of the vertices
 3123 Sentiment Analysis of the tweet:
 3124 - K-Core DFS belief_propagated_possscore: 244.140625
 3125 - K-Core DFS belief_propagated_negscore: 1.0
 3126 - Core Number belief_propagated_possscore: 419095.158577
 3127 - Core Number belief_propagated_negscore: 22888.1835938
 3128 - Above Sentiment Analysis rates the tweet with positive tonality.
 3129
 3130
 3131 185. Commits as on 25 November 2015
 3132
 3133 - New WordNetPath.py file has been added to compute the path in a WordNet graph between two words
 3134 - WordNetSearchAndVisualizer.py text generation code has been updated for importing and invoking path_between() funct
 3135 by which set of sentences are created from the RGO WordNet subgraph. This path is obtained from common hypernyms for

3136 that enhances WordNet relations. Each edge in RGO graph is made a hyperedge due to this hypernym path finding.
 3137 - logs and screenshots have been added for above
 3138
 3139 The text generated for the hypernym paths in WordNet subgraph in testlogs/ is quite primitive and sentences are conne
 3140
 3141 -----
 3142 186. Commits as on 4 December 2015
 3143 -----
 3144 All the Streaming_<>.py Streaming Algorithm implementations have been updated with:
 3145 - hashlib ripemd160 hash MD algorithm for hash functions and return hexdigest()
 3146 - USBWWAN byte stream data from USBmd print_buffer() logs has been added as a Data Storage and Data Source
 3147 - logs for the above have been added to testlogs/
 3148 - Streaming Abstract Generator has been updated with USB stream data iterable and parametrized for data source and st
 3149 - Some corrections to the scripts
 3150
 3151 -----
 3152 187. Commits as on 7 December 2015
 3153 -----
 3154 - USB stream file storage name updated in Streaming_AbstractGenerator
 3155 - Corrections to CountMinSketch - hashing updated to include rows (now the element frquencies are estimated almost ex
 3156 - logs for above updated to CountMinSketch
 3157 Added Cardinality estimation with LogLog and HyperLogLog counters for USB stream datasets
 3158 - HyperLogLog estimation: ~110 elements
 3159 - LogLog estimation: ~140 elements
 3160
 3161 -----
 3162 188. Commits as on 8 December 2015
 3163 -----
 3164 - Updated the Streaming LogLogCounter and HyperLogLogCounter scripts to accept StreamData.txt dataset from Abstract G
 3165 Spark MapReducer script for Streaming Data sets for comparison of exact data with Streaming_<algorithm>.py estimatior
 3166 - Added logs for the Counters and Spark MapReducer script on the StreamData.txt
 3167 - LogLog estimation: ~133
 3168 - HyperLogLog estimation: ~106
 3169 - Exact cardinality: 104
 3170
 3171 -----
 3172 189. (FEATURE - DONE) Commits as on 9 December 2015
 3173 -----
 3174 - New python implementation for CountMeanMinSketch Streaming Data Frequency Estimation has been added which is an imp
 3175 CountMinSketch that computes median of average of estimator rows in sketch
 3176 - Corrections to CountMinSketch hashing algorithms and Sketch width-depth as per the error bounds has been made
 3177 - Spark MapReducer prints the number of elements in the stream data set
 3178 - Logs for the above have been added to testlogs
 3179
 3180 -----
 3181 190. (FEATURE - DONE) Commits as on 11 December 2015
 3182 -----
 3183 Dependency Injection code commits for MongoDB backend - With this MongoDB is also a storage backend for AsFer algorit
 3184 - Abstract_DBBackend.py has been updated for both MySQL and MongoDB injections
 3185 - MongoDB configuration and backend connect/query code has been added. Backend is either populated by Robomongo or py
 3186 Streaming Abstract Generator iterable framework.
 3187 - With this AsFer supports both SQL(MySQL) and NoSQL(file,hive,hbase,cassandra backends in Streaming Abstract Generat
 3188 - log with a simple NoSQL table with StreamData.txt and USBWWAN data has been added to testlogs/.
 3189 - MongoDB configuration has a database(asfer-database) and a collection(asfer-collection).
 3190 - MongoDB_DBBackend @provides pymongo.collection.Collection which is @inject-ed to Abstract_DBBackend
 3191 - Abstract_DBBackend changes have been reflected in Scrapy Web Spider - backend added as argument in execute_query()
 3192 - Abstract_DBBackend.py has a subtle problem:
 3193 - Multiple @inject(s) are not supported in Python Injector
 3194 - only the innermost @inject works and outer @inject throws a __init__ argument errors in webspider/
 3195 - Conditional @inject depending on backend is required but at present switching the order of @inject(s) circu
 3196 - most recent scrapy crawl logs for this have been added to webspider/testlogs
 3197
 3198 -----
 3199 191. (THEORY) An update and additions to runtime analysis of Recursive Gloss Overlap Algorithm in TAC 2010
 3200 (http://www.nist.gov/tac/publications/2010/participant.papers/CMI_IIT.proceedings.pdf)
 3201 -----
 3202 Analysis of runtime in the link above is too cryptic. An updated analysis of steps are given here:
 3203 - Nodes at topmost level are keywords in document. For each subsequent recursion step following analysis is per keywc
 3204 - Nodes at level i-1 are computed (base case) : $x^{(i-1)}$ where x is average size of gloss definition
 3205 - Naive pairwise comparison of overlap is done at level i-1 which makes it $x^{2(i-1)}$
 3206 - Tree isomorphism algorithms can be optionally applied to reduce number of nodes getting recomputed. There are
 3207 polytime algorithms for subtree isomorphisms (www.cs.bgu.ac.il/~dekelts/publications/subtree.pdf)
 3208 - Nodes at level i-1 are reduced by Overlap(i-1) : $x^{(i-1)} - \text{Overlap}(i-1)$
 3209 - Maximum number Nodes at level i - are from gloss expansion of those at i-1 : $(x^{(i-1)} - \text{Overlap}(i-1)) * x$
 3210 - Thus total time at level i is: Time_for_pairwise_comparison_to_find_gloss_verlap + Time_for_removing_isomorphic_nod
 3211 $T(i) = \sigma([x^{(i-1)} - \text{Overlap}(i-1)]^2 + \text{subtree_isomorphism}(i))$
 3212 - Above is naively upperbounded to $O(x^{(2d)})$ [as subtree isomorphism is polynomial in supertree and subtree vertices
 3213 - If number of vertices in RGO multipartite graph (ignoring isomorphism) constructed above is $V=O(x^{(d)})$, runtime is
 3214 far less than $O(E*V^2)$ mentioned in TAC 2010 link because number of keywords in toplevel are less than number of edge
 3215 - On a related note runtime for intrinsic merit ranking of the RGO wordnet subgraph can not be equated per-se to rank
 3216 - Parallel Recursive Gloss Overlap graph construction on a cloud could reduce the runtime to $O(W*V^2/c)$ where c is si

3217
 3218
 3219
 3220
 3221 192. (FEATURE - DONE) Commits as on 14 December 2015
 3222
 3223 - New Interview Algorithm script with NetworkX+Matplotlib rendering and takes as input a randomly crawled **HTML** webpag
 3224 rip off script and style tags and write only text in the **HTML** page) has been added
 3225 - Above script also computes the graph theoretic connectivity of the RGO wordnet subgraph based on Menger's theorem -
 3226 required to disconnect the graph or equivalently number of node independent paths
 3227 - logs and screenshots for the above have been added
 3228 - WebSpider.py has been updated to crawl based on a crawling target parameter - Either a streaming website(twitter, s
 3229 **HTML** webpage
 3230
 3231 193. (FEATURE - DONE) RGO graph complexity measures for intrinsic merit of a text document - Commits as on 15 Decembe
 3232
 3233 - Interview Algorithm Crawl-Visual script has been updated with a DOT graph file writing which creates a .dot file fo
 3234 - Also variety of connectivity and graph complexity measures have been added
 3235 - Importantly a new Tree Width computing script has been added. NetworkX does not have API for tree width, hence a na
 3236 through all subgraphs and finds intersecting subgraphs to connect them and form a junction tree, has been written. Th
 3237
 3238 194. Commits as on 16 December 2015
 3239
 3240 - TreeWidth implementation has been corrected to take as input set of edges of the RGO graph
 3241 - TreeWidth for set of subgraphs less than an input parameter size is computed as TreeWidth computation is exponential
 3242 and there are MemoryErrors in python for huge set of all subgraphs. For example even a small graph with 10 nodes give
 3243 possible subgraphs
 3244 - Spidered text has been updated to create a small RGO graph
 3245 - Logs and screenshots have been added
 3246 - Each subgraph is hashed to create a unique string for each subgraph
 3247 - TreeWidth is printed by finding maximum set in junction tree
 3248
 3249 195. (THEORY) WordNet, Evocation, Neural networks, Recursive Gloss Overlap and Circuit Complexity
 3250
 3251 WordNet and Evocation WordNet are machine learning models based on findings from psychological experiments. Are WordN
 3252 related? Evocation WordNet which is network of words based on how evocative a word is of another word readily transl
 3253 This is because a machine learning abstraction of neuron - perceptron - takes weights, inputs and biases and if the l
 3254
 3255
 3256 196. (FEATURE - DONE) Mined Rule Search in Astronomical Data - Commits as on 17 December 2015
 3257
 3258 - New Mined Class Association Rule Search script has been added. This script searches the astronomical data with pars
 3259 data with date, time and longitude-latitude queries.
 3260 - Where this is useful is after mining the astronomical data with SequenceMining, there is a necessity to search wher
 3261 - Logs for this has been added in testlogs/ and chartsummary.rulesearch
 3262
 3263
 3264 197. Commits as on 18 December 2015
 3265
 3266 - Interview Algorithm crawl-visual script changed for treewidth invocation
 3267 - Spidered text changed
 3268 - Rule Search script corrected to use datetime objects
 3269 - Rule Search script corrected to use timedelta for incrementing date and time
 3270 - logs and screenshots for above
 3271 - Junction Tree for RGO graph - logs and screenshots
 3272
 3273
 3274
 3275 198. (THEORY) Star Complexity of Graphs - Complement Function circuit and Unsupervised Classification with RGO graph
 3276
 3277 Star complexity of a graph defined in [Stasys Jukna] - <http://www.thi.informatik.uni-frankfurt.de/~jukna/ftp/graph-cc>
 3278 is the minimum number of union and intersection operations of star subgraphs required to create the larger graph whi
 3279
 3280
 3281 199. (FEATURE - DONE) Tornado Webserver, REST API and GUI for NeuronRain - Commits as on 22 December 2015
 3282
 3283 Commits for NeuronRain WebServer-RESTfulAPI-GUI based on tornado in python-src/webserver_rest_ui/:
 3284 - NeuronRain entrypoint based on tornado that reads a template and implements GET and POST methods
 3285 - templates/ contains renderable html templates
 3286 - testlogs/ has neuronrain GUI logs
 3287 - RESTful API entrypoint <host:33333>/neuronrain
 3288
 3289
 3290 200. (FEATURE - DONE) NeuronRain as SaaS and PaaS - for commits above in (199)
 3291
 3292 RESTful and python tornado based Graphical User Interface entrypoint that reads from various html templates and passe
 3293 incoming concurrent requests to NeuronRain subsystems - AsFer, VIRGO, KingCobra, USBmd and Acadpdrafts - has bee addde
 3294 simplest possible POST form without too much rendering (might require flask, twisted, jinja2 etc.,) for AsFer algorit
 3295 This exposes a RESTful API for commandline clients like cURL. For example a cURL POST is done to NeuronRain as:
 3296 cURL POST: curl -H "Content-Type: text/plain" -X POST -d '{"component": "AsFer", "script": "<script_name>", "arguments": "
 3297 With this NeuronRain is Software-As-A-Service (SaaS) Platform deployable on VIRGO linux kernel cloud, cloud OSes and

3298 More so, it is Platform-As-A-Service (PaaS) when run on a VIRGO cloud.
 3299
 3300
 3301 201. (FEATURE - DONE) Apache Spark MapReduce Parallel Computation of Interview Algorithm Recursive Gloss Overlap Graph
 3302 - Commits as on 24 December 2015
 3303
 3304 - 2 python files for Spark MapReduce of Recursive Gloss Overlap graph construction has been added to repository
 3305 - These two implement Interview Algorithm Recursive Gloss Overlap graph construction and Map-Reduce functions that pa
 3306 each recursion step computing the gloss tokens from previous recursion level. This is the most important part of the
 3307 consumes lot of time in serial version along with overlap computation. Apache Spark has been recently gaining importa
 3308 - In this implementation, Resilient Distributed Dataset is the set of tokens in each recursion level and is parallell
 3309 huge Spark cluster.
 3310 - For example if Spark cluster has 10000 nodes, and each level of recursion produces X number of gloss tokens for gra
 3311 complexity in Spark is $O(X/10000)$ where as serial version is $O(X)$ with negligible network overhead. Spark has in-memc
 3312 minimizes network latency because of disk access.
 3313 - There were lot of implementation issues to make the parallelism. Map and Reduce functions use namedtuples to return
 3314 field in namedtuple, there are internal pickling issues in Py4J - Python4Java which PySpark internally invokes to get
 3315 Java side of the object wrapped as an iterable. This prevents returning multiple values - for example Synsets - in Ma
 3316 - So only tokens at a level are map-reduced and returned while the prevlevelsynsets (required for adding edges across
 3317 with a proprietary asfer_pickle_load() and asfer_pickle_dump() functions that circumvents the python and java vagari
 3318 - With proprietary pickling and Map-Reduce functions, Recursive Gloss Overlap graph has been constructed in parallel.
 3319 - Proprietary pickling is done to a text file which is also added to repository. This file is truncated at the end of
 3320 - Subtlety here is that maximum number of tokens at a recursion level $t = \text{number_of_tokens_at_level_}(t-1) * \text{maximum_s}$
 3321 which grows as $\text{series} = \text{number_of_words} * (1 + s + s^2 + s^3 + \dots + s^{t_max})$. Size of a document - number of words - c
 3322 - If size of the Spark cluster is $O(f(d)*s^{t_max})$, each recursion step is of time $O(d*s^{t_max}/f(d)*s^{t_max}) = O(d/f(d))$
 3323 - Maximum size of gloss per word (s) is also an upper-boundable constant. With constant d and t_max , size of cluster
 3324 - Example: For set of 1000 word documents with $f(d) = \log(d)$, max gloss size 5 and recursion depth 2, size of cluster i
 3325 - Above is just an estimate of approximate speedup achievable in Spark cluster. Ideally runtime in Spark cloud should
 3326 - Thus runtime upperbound in worst case is $O(n*d*s^{t_max}/f(d))$ for cluster size $O(f(d)*s^{t_max})$.
 3327 - If cluster autoscales based on number of documents also, size is a function of n and hence previous size bound is c
 3328
 3329
 3330 202. (THEORY) Recursive Gloss Overlap, Cognitive and PsychoLinguistics and Language Comprehension
 3331
 3332 Recursive Gloss Overlap algorithm constructs a graph from text documents. Presently WordNet is probably the only solu
 3333 get relations across words in a document. But the algorithm does not assume WordNet alone. Any future available algor
 3334
 3335 Intuition for Recursive Gloss Overlap for weighing natural language texts is from computational linguistics, Eye-Move
 3336
 3337 Psycholinguistics have the notion of event related potentials - when brain reacts excessively to anomalous words in r
 3338
 3339 A thought experiment of intrinsic merit versus prestige ranking:
 3340 Performance of an academic personality is measured first by accolades, awards, grades etc., which form the societal opi
 3341
 3342
 3343 References:
 3344
 3345 202.1 Circuits of the Mind - [Leslie Valiant] - <http://dl.acm.org/citation.cfm?id=199266>
 3346 202.2 Mind Grows Circuits - Lambda calculus and circuit modelling of mind - [Rina Panigrahy, Li Zhang] - <http://arxiv.org>
 3347 202.3 Psycholinguistics Electrified - EEG and SQUID Event Related Electric Potentials (ERP) peaking for anomalous wor
 3348 202.4 Word Associations and Evocations - <http://hci.cse.ust.hk/projects/evocation/index.html>
 3349 202.5 Combining WordNet, VerbNet, FrameNet - <http://web.eecs.umich.edu/~mihalcea/papers/shi.cicling05.pdf>
 3350 202.6 Computational Psycholinguistics - PoS Parsers - http://www.coli.uni-saarland.de/~crocker/courses/comp_psych/con
 3351 202.7 Brain Data for Psycholinguistics - http://personality.altervista.org/docs/14yg-al_brainsent@jlcl.pdf
 3352 202.8 ConceptNet 5 - <http://conceptnet5.media.mit.edu/>
 3353 202.9 Sanskrit WordNet - <http://www.cfilt.iitb.ac.in/wordnet/webswn/>
 3354 202.10 IndoWordNet - <http://www.cfilt.iitb.ac.in/indowordnet/index.jsp>
 3355 202.11 Brain Connectivity and Multiclass Hopfield Network - Associative memory - <http://www.umiacs.umd.edu/~joseph/W>
 3356 202.12 Text Readability Measures, Coherence, Cohesion - <http://www.readability.biz/Coherence.html>
 3357 202.13 MultiWordNet for European Languages - <http://multiwordnet.fbk.eu/english/home.php>
 3358 202.14 Coherence and Text readability indices (Coh-Metrix, FleschKincaid, Brain Overload etc.,) - <http://lingured.in1>
 3359 202.15 Readability and WordNet - <http://www.aclweb.org/anthology/008-1>
 3360 202.16. Semantic Networks (Frames, Slots and Facets) and WordNet - <http://onlinelibrary.wiley.com/doi/10.1207/s15516>
 3361 202.17 Text Network Analysis - Extracting a graph relation from natural language text - <http://noduslabs.com/publicat>
 3362 202.18 Text Network Analysis - Networks from Texts - <http://vlado.fmf.uni-lj.si/pub/networks/doc/seminar/lisbon01.pdf>
 3363 202.19 Six Degrees - Science in Connected Age - [Duncan J.Watts] - Pages 141-143 - Groundbreaking result by [Jon Klei
 3364 202.20 Align, Disambiguate, Walk distance measures - http://wwwusers.di.uniroma1.it/~navigli/pubs/ACL_2013_Pilehvar_Jui
 3365 202.21 Coh Metrix - Analysis of Text on Cohesion and Language - <https://www.ncbi.nlm.nih.gov/pubmed/15354684> - quanti
 3366 202.22 Homophily in Networks - [Duncan J.watts] - Science in Connected Age (Pages 152-153) - <https://arxiv.org/pdf/0>
 3367
 3368
 3369 203. Apache Spark MapReduce Parallel Computation of Interview Algorithm Recursive Gloss Overlap Graph Construction
 3370 - Commits as on 25 December 2015
 3371
 3372 - Added more parallelism to python-src/InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py
 3373 for computing parents (backedges in the recursion) have been added - mapFunction_Parents(), reduceFunction_Parents(),
 3374 in python-src/InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_SparkMapReducer.py
 3375 - These functions take the previous level tokens as inputs instead if synsets
 3376
 3377
 3378 204. Commits as on 28 December 2015

```

3379
3380 - Updated MapReduce functions in Spark Recursive Gloss Overlap implementation
3381
3382
3383 205. Commits as on 29 December 2015
3384
3385 - Updated python-src/InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py for choosing para
3386 serial parents backedges computation based on a boolean function.
3387 - This is because Recursive tokens mapreduce computation (Spark_MapReduce) is faster than serial version.
3388 But serial parents computation is faster than parallel parents computation ironically(Spark_MapReduce_Parents).
3389 This happens on single node Spark cluster. So, parents computation has been made configurable(serial or parallel)
3390 - Logs and Screenshots for various texts experimented have been added to testlogs/
3391 - python-src/InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_SparkMapReducer.py mapreduce uses best_matching
3392 disambiguation now which was commented earlier.
3393 - MapFunction_Parents() has a pickling problem in taking a tuple of synset objects as input arg due to which synsets
3394 causes the slowdown mentioned above compared to serial parents() version. MapFunction_Parents() has been rewritten t
3395 - Slowdown could be resolved on a huge cluster.
3396 - Thus this is a mix of serial+parallel implementation.
3397 - Logs, DOT file and Screenshots for mapreduced parents() computation
3398
3399
3400 206. Commits as on 30 December 2015
3401
3402 Some optimizations and redundant code elimination in python-src/InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMe
3403
3404
3405 207. Commits as on 31 December 2015
3406
3407 - Spark Recursive Gloss Overlap Intrinsic Merit code has been optimized and some minutiae bugs have been resolved.
3408 - Map function for parents computation in Spark cluster has been updated to act upon only the previous recursion leve
3409 by proprietary pickling of the keyword into a file storage and loading it, and not as a function argument
3410 - Problems with previous level gloss tokens were almost similar to MapReduce functions of the recursion
3411 - New pickling file for parents computation in Spark has been added
3412 - logs and screenshots have been added to testlogs
3413 - With this, Spark Intrinsic Merit computation is highly parallelized apt for large clouds
3414 - Also a parents_tokens() function that uses gloss tokens instead of synsets has been added
3415 - New pickling dump() and load() functions have been added for keyword storage
3416 - pickling is synchronized with python threading lock acquire() and release(). Shouldn't be necessary because of
3417 Concurrent Read Exclusive Write (CREW) of keyword, but for safer side to prevent Spark-internal races.
3418
3419
3420 208. Commits as on 1,2,3,4,5,6,7 January 2016
3421
3422 - Added sections 53.14, 53.15 for HLMN and PARITY 3-SAT in 53
3423 - updated spidered text
3424 - best_matching_synset() enabled in mapreduce backedges computation which accurately disambiguates the graph. Spark s
3425 significantly slower than serial version of parents() computation with only python calls probably due to costly Pythc
3426 back-and-forth stream socket reads.
3427 - logs, DOT file and screenshots for single node Spark cluster have been added to testlogs/
3428
3429
3430 209. Commits as on 8 January 2016
3431
3432 - In InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_SparkMapReducer.py increased local threads to 2 (for du
3433 all SparkContexts instantiated
3434 - Added screenshot and logs for 2 local threads SparkContext mapreduce
3435 - Reference: Berkeley EdX Spark OpenCourse - https://courses.edx.org/c4x/BerkeleyX/CS100.1x/asset/Week2Lec4.pdf
3436
3437
3438 210. Commits as on 10 January 2016
3439
3440 NeuronRain Research (SourceForge) version 2016.1.10 released.
3441
3442
3443 211. Commits as on 11 January 2016
3444
3445 Added section 53.16 for an apparent contradiction between polysize and superpolynomial size among P/poly, Percolation
3446 special case of HLMN theorem.
3447
3448
3449 212. (FEATURE - DONE) Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) - Commits as on 12 Ja
3450
3451 Python rpy2 wrapper implementation for :
3452     - Principal Component Analysis(PCA)
3453     - Singular Value Decomposition(SVD)
3454 which invoke R PCA and SVD functions and plot into 2 separate pdf files has been added to repository.
3455 Logs for an example have been added to testlogs/
3456
3457
3458 213. (FEATURE - DONE) Kullback-Leibler Divergence - Commits as on 17 January 2016
3459

```

```

3460 Kullback-Leibler Divergence implementation:
3461 -----
3462 Approximate distance between 2 probability distributions with logs
3463 in terms of weighted average distance represented as bits
3464 -----
3465 214. (FEATURE - DONE) Basic Statistics - Norms and Median - Commits as on 19 January 2016
3466 -----
3467 Implementation for basic statistics - L1, L2 norms, median etc.,
3468
3469 -----
3470 215. Commits as on 20 January 2016
3471 -----
3472 - Updated AsFer Design Document for Psycholinguistics of Reading a Text document and Recursive Gloss Overlap
3473 - Added Standard Deviation and Chi-Squared Test R functions to python-src/Norms_and_Basic_Statistics.py
3474
3475 -----
3476 216. (THEORY) Recursive Lambda Function Growth Algorithm - Psycholinguistic Functional Programming simulation of Human
3477 Example sentence:
3478 California Gas Leak Exposes Growing Natural Gas Risks.
3479
3480 A left-right scan of the human reading groups the sentence into set of phrases and connectives and grows top-down glc
3481 p1 - California Gas Leak
3482 p2 - Exposes
3483 p3 - Growing Natural Gas Risks
3484
3485 For each phrase left-right, meaning is created by recursive gloss overlap disambiguated graph construction top-down (
3486 p1 - graph g1
3487 p2 - graph g2
3488 p3 - graph g3
3489
3490 Prefix graph construction and functional programming:
3491 Above sentence has three prefix phrases and graphs- p1, p1-p2, p1-p2-p3 in order (and g1, g1-g2, g1-g2-g3). As reader
3492
3493 This formulation does not depend on just semantic graphs - graphs g1,g2 and g3 could be functional programming subrou
3494 p1 - function g1 - california_gas_leak()
3495 p2 - function g2 - exposes()
3496 p3 - function g3 - growing_natural_gas_risks()
3497 f3 = f2(f1(g1,g2),g3)
3498
3499 How functions f1,f2,g1,g2,g3 are internally implemented is subjective. These functions are dynamically created and ev
3500
3501 As an ideal human sense of "meaning" stored in brain is vague and requires a "Consciousness and Freewill" theory, onl
3502
3503 Learning theory perspective of the previous - From Linial-Mansour-Nisan theorem , class of boolean functions of n var
3504
3505 References:
3506 -----
3507 216.1 Eye Movement Tracking - https://en.wikipedia.org/wiki/Psycholinguistics#Eye-movements
3508 216.2 Eye Movements in Text Comprehension - Fixations, Saccades, Regressions - http://www.jove.com/video/50780/using
3509 216.3 Symbol Grounding Problem and learning from dictionary definitions - http://aclweb.org/anthology//W/W08/W08-200
3510 216.4 TextGraphs - graph representation of texts - https://sites.google.com/site/textgraphs2017/
3511 216.5 Symbol Grounding Problem - http://users.ecs.soton.ac.uk/harnad/Papers/Harnad/harnad90.sgproblem.html - " ...
3512 216.6 Understanding Natural Language - [Terry Winograd] - https://dspace.mit.edu/handle/1721.1/7095#files-area - Chap
3513
3514
3515
3516
3517 217. Commits as on 21 January 2016
3518 -----
3519 - Corrected Chi-squared test input args
3520 - logs added to testlogs/
3521
3522
3523 218. Commits as on 27 January 2016
3524 -----
3525 Updated Sections 14 and 216.
3526
3527
3528 219. Commits as on 29 January 2016
3529 -----
3530 - Uncommented both commandlines in cpp-src/asferpythonembedding.sh
3531
3532 220. (FEATURE - DONE) Python-C++-VIRGOKernel and Python-C-VIRGOKernel boost::python and cpython implementations:
3533 -----
3534 - It is a known idiom that Linux Kernel and C++ are not compatible.
3535 - In this commit an important feature to invoke VIRGO Linux Kernel from userspace python libraries via two alternativ
3536 - In one alternative, C++ boost::python extensions have been added to encapsulate access to VIRGO memory system calls
3537 - In the other alternative, C Python extensions have been added that replicate boost::python extensions above in C -
3538 works exceedingly well compared to boost::python.
3539 - This functionality is required when there is a need to set kernel analytics configuration variables learnt by AsFer
3540 dynamically without re-reading /etc/virgo_kernel_analytics.conf.

```

```

3541 - This completes a major integration step of NeuronRain suite - request travel roundtrip to-and-fro top level machine
3542 code and rock-bottom C linux kernel - bull tamed ;-).
3543 - This kind of python access to device drivers is available for Graphics Drivers already on linux (GPIO - for accessi
3544 - logs for both C++ and C paths have been added in cpp_boost_python_extensions/ and cpython_extensions.
3545 - top level python scripts to access VIRGO kernel system calls have been added in both directories:
3546     CPython - python cpython_extensions/asferpythonextensions.py
3547     C++ Boost::Python - python cpp_boost_python_extensions/asferpythonextensions.py
3548 - .so, .o files with build commandlines(asferpythonextensions.build.out) for "python setup.py build" have been added
3549 in build lib and temp directories.
3550 - main implementations for C++ and C are in cpp_boost_python_extensions/asferpythonextensions.cpp and cpython_extensi
3551
3552 - Schematic Diagram:
3553 -----
3554     AsFer Python -----> Boost::Python C++ Extension -----> VIRGO memory system calls -----> VIRGO Linux Kerne
3555     / \
3556     |
3557     -----<----->-----<----->-----<----->
3558     AsFer Python -----> CPython Extensions -----> VIRGO memory system calls -----> VIRGO Linux Kernel Memory
3559     / \
3560     |
3561     -----
3562
3563
3564 221. Commits as on 2 February 2016
3565 -----
3566 - Uncommented PyArg_ParseTuple() to read in the key-value passed from Python layer
3567 - Unified key-value in Python layer and within CPython code with : delimiter
3568 - added Py_BuildValue() to return vuid - VIRGO Unique ID - to python and commented virgo_free() so that a parallel cc
3569 can connect to kmem cache and do a virgo_get on this vuid - this is a precise scenario where Read-Copy-Update fits in
3570 multiple versions can co-exist at a time
3571 - Specific to NeuronRain Research version - experimental - for GRAFIT training materials:
3572     - separated VIRGO system calls into set and get kernel analytics python module functions
3573     - Python asferpythonextensions.py has been updated with 2 functions for get and set
3574     - Logs for this have been added along with a weird error noticed which is unrelated to this and
3575 occurs in USB driver that too in Wi-Fi when USB device is not active
3576 - All VIRGO system calls work in this segregated version similar to unified CPython
3577 code in NeuronRain enterprise GitHub codebase
3578
3579
3580 222. (THEORY) Recursive Lambda Function Growth Algorithm - 216 elaborated with examples
3581 -----
3582 Boolean function learning and PAC learning are special cases of this Lambda function learning algorithm because any
3583 intermediate lambda function can be a boolean function too.
3584
3585 Algorithms steps for English Natural Language Processing - Parallel read:
3586 -----
3587 - Approximate midpoint of the sentence is known apriori
3588 - Language specific connectives are known apriori (e.g is, was, were, when, who etc.,)
3589 - Sentence is recursively split into phrases and connectives and converted into lambda functions with balanced number
3590 - Root of each subtree is unique name of the function
3591
3592 Example Sentence1:
3593 -----
3594 PH is infinite relative to random oracle.
3595
3596 Above sentence is translated into a lambda function composition tree as:
3597 relative(is(PH, infinite), to(random,oracle))) which is a tree of depth 3
3598
3599 In this example every word and grammatical connective is a lambda function that takes some arguments and returns a pa
3600
3601 Example Sentence2:
3602 -----
3603 Farming and Farmers are critical to success of a country like India.
3604
3605 Above sentence is translated into a lambda function composition tree as:
3606 Critical(are(and(Farming,Farmers)), a(success(to,of), like(country, India)))
3607
3608 This composition is slightly different from Part-of-Speech trees and inorder traversal of the tree yields original se
3609 As functions are evaluated over time period, at any time point there is a partially evaluated composition prefix tree
3610 rest of the sentence to be translated yet - these partial trees have placeholder templates that can be filledup by a
3611 from rest of the sentence.
3612
3613 Each of these lambda functions can be any of the following but not limited to:
3614 - Boolean functions
3615 - Generic mathematical functions
3616 - Neural networks (which include all Semantic graphs like WordNet etc.,)
3617 - Belief propagated potentials assigned by a dictionary of English language and computed bottom-up
3618 - Experimental theory of Cognitive Psycholinguistics - Visuals of corresponding words - this is the closest simulatio
3619
3620
3621     Mobile phones operate through towers in each cellular area that transmit signals.

```

```

3622 with its per-word lambda function composition tree :
3623
3624     in(operate(mobile phones, through(tower)), that(each(cellular area), transmit(signals)))
3625
3626 evokes from left-to-right visuals of Mobile phones, towers, a bounded area in quick succession based on user's person
3627
3628 The language of Sanskrit with Panini's Grammar fits the above lambda calculus framework well because in Sanskrit case
3629     Sambhala Grama Mukhyasya VishnuYashas Mahatmana: ... ( Chieftain of Sambhala Village, VishnuYashas the great
3630
3631 can be rearranged and shuffled without altering the meaning, a precise requisite for lambda function composition tree
3632
3633 As an alternative to WordNet:
3634
3635 Each lambda function carries dictionary meaning of corresponding word with placeholders for arguments.
3636 For example, for word "Critical" corresponding lambda function is defined as:
3637     Critical(x1,x2)
3638 If dictionary meanings of critical are defined with placeholders:
3639     1) Disapproval of something -
3640     2) - is Important to something -
3641 there is a need for disambiguation and 2) has to be chosen based either on number of arguments or disambiguation usir
3642     x1 is important to something x2
3643 Thus WordNet can be replaced by something more straightforward. These steps can be recursed top-down to expand the me
3644
3645 This algorithm accepts natural languages that are between Context Free Languages and Context Sensitive Languages.
3646
3647 References:
3648 222.1 Charles Wikner - Introductory Sanskrit - http://sanskritdocuments.org/learning\_tutorial\_wikner/
3649 222.2 Michael Coulson - Teach yourself - Sanskrit - http://www.amazon.com/Complete-Sanskrit-Teach-Yourself-Language/c
3650
3651
3652
3653 223. (FEATURE - DONE) Crucial commits for Performance improvements and Cython build of Spark Interview algorithm impl
3654 - Commits as on 4 February 2016
3655
3656 - New setup.py has been added to do a Cythonized build of PySpark Interview algorithm MapReduce script
3657 - Commandline for cython build: python setup.py build_ext --inplace
3658 - This compiles python spark mapreduce script into a .c file that does CPython bindings and creates .o and .so files
3659 - FreqDist has been commented which was slowing down the bootstrap
3660 - MapReduce function has been updated for NULL object checks
3661 - Thanks to Cython, Performance of Spark MapReduce has performance shootup by factor of almost 100x - Spark GUI job e
3662 shown for this interview execution is ~10 seconds excluding GUI graph rendering which requires few minutes. This was
3663 - With Cython ,essentially Spark-Python becomes as fast as C implementation.
3664 - DOT file, Output log, Spark logs and Screenshot has been added
3665 - This completes important benchmark and performance improvement for Recursive Gloss Overlap Graph construction on lc
3666 cluster.
3667
3668
3669 Commits as on 5 February 2016
3670
3671
3672 224. Further optimizations to Spark-Cython Interview algorithm implementation:
3673
3674 - webspidered text for RGO graph construction updated
3675 - PySpark-Cython build commandlines added as a text file log
3676 - Commented unused python functions - shingling and jaccard coefficient
3677 - threading.Lock() Spark thread pickling synchronizer variable made global in MapReducer
3678 - renamed yesterday's logs and screenshot to correct datetime 4 February 2016
3679 - Added a new special graph node ["None"] for special cases when no parents are found in backedges computation in Map
3680 default root in the RGO graph as shown in matplotlib networkx graph plot
3681 - Spark logs show time per RDD job - an example MapReduce job takes 335 milliseconds
3682 - Tried Cythonizing InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py but there is a serious cython compile
3683 Matplotlib-PyQt. Hence those changes have been backed out.
3684 - DOT file and Cython C file have been updated
3685
3686
3687 225. Commits as on 8 February 2016
3688
3689 - PySpark-Cythonized Interview Algorithm implementation generated graph has been pruned to remove edges involving "Nor
3690 added during Spark MapReduce based on a config variable.
3691 - Logs and Screenshots for the above have been added to testlogs/
3692 - Some benchmark results parsed from the Spark logs with commandline - "for i in `grep Finished InterviewAlgorithmWith
3693     - Total time in milliseconds - 99201
3694     - Number of jobs - 113
3695     - Average time per mapreduce job in milliseconds - 877
3696 Thus a merit computation of sample document with few lines (33 keywords) requires ~100 seconds in local Spark cluster
3697
3698
3699 226. (THEORY) Graph Edit Distance in Interview Algorithm, PySpark-Cython Interview Algorithm benchmarks and Merit in
3700 Lambda Function Growth Algorithm
3701
3702 Interview Algorithm to assess merit, throughout this document, refers to 3 algorithms - Citation graph maxflow(which

```

3703 Previous benchmarks for PySpark-Cython parallel interview algorithm implementation could scale significantly on a clu
 3704
 3705 Computing Intrinsic Merit of a text with Recursive Lambda Function growth could involve multitude of complexity notic
 3706 - Depth of Composition tree for a text
 3707 - Size of resultant lambda function composition e.g size of WordNet subgraphs, neural nets, complexity of cont
 3708 - In essence, this reduces to a lowerbound of lambda function composition - boolean circuit lowerbounds are sp
 3709
 3710
 3711
 3712 227. (THEORY) Thought Versioning - ThoughtNet and EventNet - Psychophilosophical Digression - Might have
 3713 some parallels in Philosophical Logic - related to points (70-79)
 3714
 3715 (*) This postulates an experimental model for a "Logical Brain". It makes no assumptions about neural synapses, firir
 3716
 3717 (*) ThoughtNet is built over time from inception of life - books a person reads, events in life, interactions etc., -
 3718
 3719 (*) Thought Versioning System - tentatively named ThoughtNet - mentioned in 227 is a generalization of Evocation Word
 3720
 3721 (*) An approximate parallel to ThoughtNet versioning is the Overlay FileSystems in Unixen. Overlay filesystems store
 3722
 3723 (*) EventNet when unified with ThoughtNet makes a cosmic storage repository, all pervasive. Thoughts are stored with
 3724
 3725 (*) For example, an event with pleasant happening might be stored with high potential of positive polarity as against
 3726
 3727 (*) EventNet is a cosmic causality infinite graph with partaker nodes whereas ThoughtNet is per partaker node. This e
 3728
 3729 (*) EventNet is a parallelly created Causality graph - event vertices occur in parallel across universe and causation
 3730
 3731 (*) Previous evocation model with HMM or maximum potential need not be error-free - it can be derailed since human ur
 3732
 3733 Thought experiment for this defective disambiguation is as below
 3734
 3735 (*) Example Sentence 1: "Love at first sight is the best". Considering two persons reading this sentence with drastic
 3736
 3737 (*) Example Sentence 2: "You are too good for any contest". This sentence has sarcastic tone for a human reader. But
 3738
 3739 (*) Example Poetry 3 - lambda evaluation with shuffled connectives, is shown below with nested parenthesization - Eac
 3740 ("The time has come,") (the Walrus said),
 3741 ("To talk of many things:
 3742 (Of shoes--and ships--and sealing-wax--)
 3743 (Of cabbages--and kings--)
 3744 And (why (the sea is boiling hot--))
 3745 And (whether (pigs have wings.")))
 3746 This lambda composition itself can be classified in classes viz., "time", "poetry", "sea" etc., (in special case of g
 3747
 3748 (*) Perfect design of Psycholinguistic text comprehension must involve ego-centric theory specific to each reader as
 3749
 3750 (*) Above exposition is required to get to the bottom of difficulties in formalising "what is meant by meaning" and "
 3751
 3752 (*) If ThoughtNet begot EventNet by anthropic principle, there is a possibility language was born before something ex
 3753
 3754 (*) Another counterexample: A cretan paradox like sentence - "This sentence is a lie" - which is true if it is false
 3755
 3756 (*) If there are two levels of Truth/Falsehoods similar to stratified realities defined in <https://sites.google.com/s>
 3757 - This sentence is a lie - true - self-refuting and circular
 3758 - This sentence is a lie - TRUE - not self-refuting because TRUE transcends "true"
 3759 - This sentence is a lie - false - self-refuting and circular
 3760 - This sentence is a lie - FALSE - not self-refuting because FALSE transcends "false"
 3761
 3762 (*) (QUITE PRESUMPTIVE, THIS MIGHT HAVE A PARALLEL IN LOGIC BUT COULDN'T FIND IT) In other words, the sentence "(It i
 3763
 3764 (*) Above philosophical dissection of meaning has striking similarities to quantum mechanics - If language has substr
 3765
 3766 (*) Levels of Truth are reminiscent of Tarski's Undefinability of Truth Theorem - <https://plato.stanford.edu/entries/>
 3767
 3768
 3769 228. (THEORY) Bose-Einstein Condensate model for Recursive Gloss Overlap based Classification
 3770
 3771 Bose-Einstein condensate fitness model by [Ginestra Bianconi] described in 18.10 for any complex network graph is:
 3772 Fitness of a vertex = $2^{(-b*Energy)}$ where b is a Bose-Einstein condensate function.
 3773
 3774 Here fitness of a vertex is defined as ability to attract links to itself - Star complexity. It is not known if abili
 3775
 3776 Applying the above model to a relational graph obtained from text document implies graph theoretic representation of
 3777
 3778 Analogy: Recursive Gloss Overlap graph can be construed as a 3 dimensional rubbersheet with low energy words as troug
 3779
 3780 Reference:
 3781
 3782 228.1 Linked [Albert Laszlo Barabasi] - Chapter 8 - Einstein's Legacy
 3783


```

3865 each of the 10 neurons
3866 - Logs for this have been committed to testlogs
3867 - Logs show a marked swing in Maxpooling map where the segments of pattern "3" are pronounced.
3868 - Final neural layer shows a variegated decision from each neuron for corresponding 3 convolution maps
3869
3870 -----
3871 237. (FEATURE-DONE) Commits as on 14 March 2016
3872 -----
3873 - Some bugs resolved
3874 - Added one more example with no pattern
3875 - Convolution is computed for all 3 bitmap examples
3876 - Final neuron layer now is a function of each point in all maxpooling layers
3877 - The existence of pattern is identified by the final output of each of 10 neurons
3878 - Patterns 0 and 3 have a greater neural value than no pattern. Gradation of neural value indicates intensity of
3879 - Above is a very fundamental pattern recognition for 2 dimensional data. Sophisticated deconvolution is explaine
3880 - 3 logs for this commit have been included in testlogs/
3881 - random weighting has been removed.
3882
3883
3884 238. (THEORY) Deep Learning Convolution Network and a boolean function learning algorithm of different kind
3885 -----
3886 Deep Learning Convolution Network for Image Pattern Recognition elicits features from the image considered as 2-dimer
3887
3888
3889 239. (FEATURE-DONE) Commits as on 15 March 2016
3890 -----
3891 - DeepLearning BackPropagation implementation:
3892   - An example Software Analytics usecase for CPU and Memory usage has been included
3893   - Number of Backpropagation weight update iterations has been increased 10 fold to 3000000.
3894   - logs for some iterations have been included in testlogs/
3895 - DeepLearning Convolution Network implementation:
3896   - Image patterns have been changed to 0, 8 and no-pattern.
3897   - Final neuron layer weights have been changed by squaring to scale down the output - this differentiates pat
3898   - logs for this have been included in testlogs/
3899
3900
3901 240. (THEORY and IMPLEMENTATION) ThoughtNet and Reinforcement Learning
3902 -----
3903 Reinforcement Learning is based on following schematic principle of interaction between environment and agent learnin
3904
3905           -----> ThoughtNet context (environment)
3906           |           |           | reward and state transition (most
3907           |<----- Text Document (agent) -----<----- |
3908
3909 Schematic above illustrates text document study as reinforcement learning. During left-right reading of text, evocati
3910   - 1) First coin flip -  $Pr(\text{doubling1}) = 0.5$ ,  $Pr(\text{bankrupt1}) = 0.5$ 
3911   - 2) Second coin flip -  $Pr(\text{bankrupt2}) = Pr(\text{bankrupt1}) * 0.5 = 0.25$ 
3912   - 3) Third coin flip -  $Pr(\text{bankrupt3}) = Pr(\text{bankrupt2}) * 0.5 = 0.125$ 
3913   ...
3914 By union bound probability of gambler going bankrupt after infinite number of coin flips is 1. This convergence to 1
3915
3916 A ThoughtNet Reinforcement Learning implementation has been committed as part of python-src/DeepLearning_Reinforcemer
3917
3918 References:
3919 -----
3920 241.1 Reinforcement Learning - [Richard Sutton] - http://webdocs.cs.ualberta.ca/~sutton/book/the-book.html, https://u
3921
3922
3923 241. (FEATURE-BENCHMARK-DONE) Interview Algorithm PySpark-Cython implementation benchmark with and without Spark conf
3924
3925 This benchmark is done with both:
3926 InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py
3927 InterviewAlgorithmWithIntrinsicMerit_SparkMapReducer.py
3928 both precompiled with Cython to create .c source files and .so libraries.
3929
3930 Number of keywords in newly crawled web page: 35
3931
3932 -----
3933 With spark-defaults.conf :
3934
3935 Execution 1:
3936 -----
3937 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3938 > do
3939 > sum=$(expr $sum + $i)
3940 > done
3941
3942 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3943 243058
3944 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3945 156

```

```

3946 Per task time in milliseconds: ~1558
3947
3948 -----
3949 Execution 2:
3950 -----
3951 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3952 > do
3953 > sum=$(expr $sum + $i)
3954 > done
3955 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3956 520074
3957 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3958 312
3959 Per task time in milliseconds: ~1666
3960
3961 -----
3962 Without spark-defaults.conf
3963 -----
3964 Execution 3:
3965 -----
3966 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3967 69691
3968 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
3969 156
3970 Per task time in milliseconds: ~446 which is twice faster than earlier benchmark done in February 2016 and almost 4 t
3971
3972 A spark-defaults.conf file has been committed to repository (Reference: http://spark.apache.org/docs/latest/configuration.html#spark-defaults)
3973
3974 -----
3975 242. Commits (1) as on 16,17 March 2016
3976 -----
3977 PySpark-Cython Interview Algorithm for Merit - Benchmark
3978 -----
3979 - 3 executions with and without spark-defaults.conf config settings have been benchmarked
3980 - Cython setup.py has been updated to compile both InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py and Ir
3981 to create .c and .so files
3982 - Benchmark yields some intriguing results:
3983     - Executions with spark-defaults.conf enabled are 4 times slower than executions without spark-defaults.conf
3984     - Execution without spark config is twice faster than earlier benchmark
3985 - Logs and screenshots for above have been committed to testlogs
3986 - Text document has been recrawled and updated (number of keywords almost same as previous benchmark)
3987 - Spark config file has been committed
3988
3989 -----
3990 PySpark-Cython Interview Algorithm for Merit - Benchmark
3991 -----
3992 - 3 executions with and without spark-defaults.conf config settings have been benchmarked
3993 - Cython setup.py has been updated to compile both InterviewAlgorithmWithIntrinsicMerit_Crawl_Visual_Spark.py and Ir
3994 to create .c and .so files
3995 - Benchmark yields some intriguing results:
3996     - Executions with spark-defaults.conf enabled are 4 times slower than executions without spark-defaults.conf
3997     - Execution without spark config is twice faster than earlier benchmark
3998 - Logs and screenshots for above have been committed to testlogs
3999 - Text document has been recrawled and updated (number of keywords almost same as previous benchmark)
4000 - Spark config file has been committed
4001
4002 -----
4003 243. Commits (2) as on 16,17 March 2016
4004 -----
4005 More benchmarking of PySpark-Cython Intrinsic Merit computation
4006 -----
4007 - Enabled Spark RDD cacheing with cache() - storage level MEMORY
4008 - Recompiled .c and .so with Cython
4009 - uncommented both lines in Cython setup.py
4010 - logs and screenshots for above have been committed in testlogs/
4011 - locking.acquire() and locking.release() have been commented
4012 - With this per task duration has been brought down to ~402 milliseconds on single node cluster. Ideally on a multicore
4013 when tasks are perfectly distributable, this should be the runtime.
4014
4015 -----
4016 With spark-defaults.conf - multiple contexts disabled and reuse worker enabled
4017 -----
4018 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4019 246796
4020 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4021 156
4022 Per task time milliseconds: ~1582
4023
4024 -----
4025 Without spark-defaults.conf - locking.acquire()/release() disabled and Spark RDD cacheing enabled
4026

```

```

4027 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4028 248900
4029 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4030 618
4031 Per task time milliseconds: ~402 (fastest observed thus far per task; Obviously something is wrong with spark-default
4032
4033 -----
4034 244. (FEATURE-BENCHMARK-DONE) Interview Algorithm PySpark-Cython implementation benchmark with Spark configurables
4035 - Commits as on 21 March 2016
4036 -----
4037 Following benchmark was done with a new spark-defaults.conf (committed as spark-defaults2.conf):
4038
4039 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4040 965910
4041 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4042 618
4043 Time per task in milliseconds: ~1562 (Again, with spark-defaults.conf with some additional settings, there is a block
4044
4045 -----
4046 245. (THEORY) Learning a variant of Differential Privacy in Social networks
4047 -----
4048 Nicknames/UserIds in social media are assumed to be unique to an individual. Authentication and authorization with Pu
4049 is assumed to guarantee unique identification. In an exceptional case, if more than one person shares a userid intent
4050
4051 -----
4052 246. (FEATURE-DONE) Commits as on 24 March 2016 - Code Optimizations - Cacheing and Loop invariant - Interview Algori
4053 -----
4054 - New Cacheing datastructures have been included for storing already found previous level backedge vertices for each
4055 already found gloss tokens. Presently these caches are python dictionaries only and in a distributed setting this can
4056 object key-value stores like memcached.(InterviewAlgorithm/InterviewAlgorithmWithIntrinsicMerit_SparkMapReducer.py)
4057 - There was an inefficient loop invariant computation for prevelevesynsets_tokens which has been moved to outermost w
4058 - spark-default2.conf has been updated with few more Spark config settings
4059 - Spidered text has been recrawled
4060 - logs and screenshots for this commits have been included in testlogs/
4061 - Cython .c , .so files have been rebuilt
4062 - Cacheing above in someway accomplishes the isomorphic node removal by way of Cache lookup
4063
4064 -----
4065 247. (FEATURE-BENCHMARK-DONE) Intrinsic Merit PySpark-Cython implementation - With and Without cacheing
4066 - Commits as on 25 March 2016
4067 -----
4068 1.Cache md5 hashkey has been changed to be the complete tuple (tokensofprevlevel,keyword) - the rationale is to have
4069 uniqueness to find backvertices for a keyword and gloss from previous recursion step.
4070 2.Following benchmark was done by disabling and enabling lookupCache and lookupCacheParents boolean flags.
4071 3.Cache values are "NoValue" string literals by default initialized in lambda and the Cache updates are not append()s
4072 simple key-value assignments.
4073 --
4074 Number of keywords: 7
4075 Without Cacheing: 9 minutes for all tasks (including NetworkX and graphics rendering times which is quite considerable)
4076 With Cacheing: 9 minutes for all tasks (including NetworkX and graphics rendering times which is quite considerable)
4077
4078 Summation of individual task times in milliseconds and averaging sometimes gives misleadingly high duration per task
4079 total execution is faster. Because of this start-end time duration is measured. For above example Cacheing has no eff
4080 there are no repetitions cached to do lookup. Logs and screenshots with and without cacheing have been committed to t
4081
4082 -----
4083 248. (THEORY) An alternative USTCONN LogSpace algorithm for constructing Recursive Gloss Overlap Graph
4084 -----
4085 Benchmarks above are selected best from multiple executions. Sometimes a mysterious slowdown was observed with both C
4086 load which could be result of JVM Garbage Collection for Spark processes among others. These benchmarks are thus just
4087
4088 -----
4089 249. Commits as on 29 March 2016
4090 -----
4091 - New subroutine for printing WordNet Synset Path between 2 words - this prints edges related by hypernyms and hypony
4092 - an example log has been committed in testlogs/
4093
4094 From the example path in logs, distance is more of a metapath than a thesaurus-like path implemented in Recursive Glc
4095
4096 -----
4097 250. (FEATURE-DONE) Commits (1) as on 30 March 2016 - MemCache Integration with Spark-Cython Intrinsic Merit Computat
4098 -----
4099 - In this commit, native python dictionary based cache lookup for Spark_MapReduce() and Spark_MapReduce_Parents() is
4100 standard MemCache Distributed Object Cacheing get()/set() invocations.
4101 - Logs and Screenshots for above have been committed to testlogs/
4102 - Prerequisites are MemCached (ubuntu apt package) and Python-memcache (pip install) libraries
4103 - a recrawled webpage has been merit-computed
4104 - MemCached is better than native dict(s) because of standalone nature of Cache Listener which can be looked up from
4105 anywhere on cloud
4106
4107 -----

```

```

4108 251. (FEATURE-DONE) Commits (2) as on 30 March 2016 - Spark-Cython Intrinsic Merit computation with spark-defaults.cc
4109 -----
4110 - spark-defaults2.conf has been enabled with extra java options for performance (reference: http://docs.oracle.com/j
4111 - lookupCache and lookupCacheParents boolean flags have been done away with because memcache has been enabled by defa
4112 - With this spark logs show more concurrency and less latency. Dynamic allocation was in conflict with number of exec
4113 - text document has been updated to have ~10 keywords. This took almost 7 minutes which looks better than one with sp
4114 - Screenshot and logs have been committed in testlogs/
4115 -----
4116 252. (FEATURE-DONE) Commits as on 1 April 2016
4117 -----
4118 Loopless Map function for Spark_MapReduce()
4119 -----
4120 - new Map function MapFunction2() has been defined which doesn't loop through all keywords per level, but does the gl
4121 which is aggregated by Reduce step. MapFunction() does for loop for all keywords per level.
4122 - a dictionary cacheing with graphcachelocal has been done for lookup of already gloss-tokenized keywords. This could
4123 resets the graphcachelocal to a null which shouldn't have.
4124 - This has a execution time of 6 minutes overall for all tasks compared to for-loop Map function in Spark_MapReduce()
4125 - logs and screenshots for Loopless Map with and without graphcachelocal have been committed
4126 - Rebuilt Cython .c, .o, .so, intrinsic merit log and DOT files
4127 -----
4128 253. (THEORY) Hypercontractivity - Bonami-Beckner Theorem Inequality, Noise Operator and p-Norm of Boolean functions
4129 -----
4130 Hypercontractivity implies that noise operator attenuates a boolean function and makes it close to constant function.
4131 defined as:
4132      $|Trho|_q \leq |f|_p$  where  $0 \leq rho \leq \sqrt{((p-1)(q-1))}$  for some p-norm and q-norm
4133 and in its expanded form as:
4134      $\sigma(rho^{|S|} * (1/2^n * \sigma(|f(x)|^q * (-1)^{parity(x)})))^{(1/q)} * parity(S) \leq (1/2^n * \sigma(|f(x)|^p))^{(1/p)}$ 
4135 Hypercontractivity upperbounds a noisy function's q-norm by same function's p-norm without noise. For 2-norm, by Pars
4136 -----
4137 Reference:
4138 -----
4139 253.1 Bonami-Beckner Hypercontractivity - http://theoryofcomputing.org/articles/gs001/gs001.pdf
4140 -----
4141 254. (THEORY) Hypercontractivity, KKL inequality, Social choice boolean functions - Denoisification 3
4142 -----
4143 For 2-norm, Bonami-Beckner inequality becomes:
4144      $\sigma((rho^{|S|} * fourier_coeff(S)^2)^{2/2}) \leq [1/2^n * (\sigma(f(x))^p)^{2/p}]$ 
4145 -----
4146 For boolean functions  $f: \{0,1\}^n \rightarrow \{-1,0,1\}$ , [Kahn-Kalai-Linial] inequality is special case of previous:
4147     For  $rho=p-1$  and  $p=1+\delta$ ,  $\sigma(delta^{|S|} * fourier_coeff(S)^2) \leq (Pr[f!=0])^{2/(1+\delta)}$ 
4148 where p-norm is nothing but a norm on probability that  $f$  is non-zero (because  $Pr[f!=0]$  is a mean of all possible  $f(x)$ )
4149 -----
4150 From 53.12 size of a noisy boolean function circuit has been bounded as:  $\sum(rho^{|S|} * fourier_coeff(S)^2) * 2^{(n)}$ 
4151 for  $|S| > t$ . From KKL inequality, 2-norm in LHS can be set to maximum of  $(Pr[f!=0])^{2/(1+\delta)}$  in 53.12 and Size low
4152 a denoisified circuit:
4153      $(Pr[f!=0])^{2/(1+\delta)} * 2^{((t^{(1/\delta)})/20) - 1} \leq \text{Size}$ 
4154 which is exponential when  $\delta=1$  and  $Pr[f!=0]$  is quite close to 1 i.e  $f$  is 1 or -1 for most of the inputs.
4155 -----
4156 If  $f$  is 100% noise stable, from Plancherel theorem:
4157      $\sigma(rho^{|S|} * f(S)^2) = 1$ ,  $S$  in  $[n]$ 
4158     For  $|S| < t=n$ ,  $1 - \sum(rho^{|S|} * fourier_coeff(S)^2) \leq 2 * (\text{Size}) * 2^{(-t^{(1/\delta)})/20}$ 
4159     But for  $rho=p-1$  and  $p=1+\delta$ ,  $1 - \sum(delta^{|S|} * fourier_coeff(S)^2) > 1 - (Pr[f!=0])^{2/(1+\delta)}$  from KKL
4160     For  $|S| < t=n$ ,  $1 - (Pr[f!=0])^{2/(1+\delta)} < 1 - \sum(rho^{|S|} * fourier_coeff(S)^2) \leq 2 * (\text{Size}) * 2^{(-t^{(1/\delta)})/20}$ 
4161      $\Rightarrow 0.5 * (1 - (Pr[f!=0])^{2/(1+\delta)}) * 2^{(t^{(1/\delta)})/20} < 0.5 * (1 - \sum(rho^{|S|} * fourier_coeff(S)^2)) * 2^{(t^{(1/\delta)})/20} \leq \text{Size}$ 
4162 -----
4163 Again denoisification by letting  $rho$  and  $\delta$  tend to 0 in above, places an exponential lowerbound, with constant up
4164 -----
4165 PH in  $P^{\#P}$  in  $P/Poly \Rightarrow P^{\#P} = MA$ . (assumption:  $NC/Poly$  is in  $P/Poly$  because any logdepth, polysize bounded fanin circu
4166 NC/log percolation circuit would imply collapse of polynomial hierarchy - RHS PH-complete is lowerbounded by LHS NC/l
4167 -----
4168 Percolation boolean functions have a notion of revealment - that is, there exists a randomized algorithm correspondin
4169      $\sigma(fourier_coeff(S)^2) \leq \text{revealment} * \text{constant} * 2\text{-norm}(f)$ 
4170 -----
4171 There is a special case in which size of advice list can be brought down to  $\log n$  for  $Z(n)$  grid. Set of logn pc
4172 -----
4173 Reference:
4174 -----
4175 254.1 Randomized Algorithms and Percolation - http://math.univ-lyon1.fr/~garban/Slides/Newton.pdf
4176 -----
4177 255. (THEORY) Majority Voting in Multipartisan Elections
4178 -----
4179 Uptill now, P(Good) majority voting in this document describes only 2-candidate elections with a majority function  $vc$ 
4180 Noise stability of a voter's decision boolean function is assumed as a suitable measure of voter/voting error in RHS
4181 generic RHS is when there is a multiway contest and error is bounded. P(Good) binomial summation still applies for mu
4182     - Individual Voter Judging Functions which are not boolean functions and
4183     - Generic Majority Function that needs to find most prominent index from an assorted mix of votes (Heavy hitt
4184     - There are three variables - number of variables per voter, number of voters and number of candidates (which
4185

```

```

4189 Voter judging functions have to choose an index within n candidates than simple 0-1. In a special case non-boolean fu
4190
4191
4192 Reference:
4193 -----
4194 255.1. Elections can be manipulated often - [Friedgut-Kalai-Nisan] - http://www.cs.huji.ac.il/~noam/apx-gs.pdf
4195 255.2. Computational Hardness of Election Manipulation - https://www.illc.uva.nl/Research/Publications/Reports/MoL-26
4196 -----
4197
4198 256. Commits as on 4 April 2016
4199 -----
4200 - Updated AsFer Design Document - KKL inequality and Denoisification
4201 - Spark-Cython intrinsic merit computation has been md5hash enabled again since there were key errors with large stri
4202 - logs and screenshots have been committed to testlogs/
4203 - rebuilt Cython .c, .so files
4204 - Spidered text has been changed - This took 28 minutes for ~40+ keywords better than 7 minutes for ~10 keywords earl
4205
4206 -----
4207 257. (FEATURE-BENCHMARK-DONE) Analysis of PySpark-Cython Intrinsic Merit Computation Benchmarks done so far
4208 -----
4209 From 191 and 201 time complexity analysis of Recursive Gloss Overlap algorithm, for single node dualcore cluster foll
4210 runtime bound:
4211  $O(n^d * s^t * tmax / cpus)$ 
4212 where d is the number of keywords, n is the number of documents and s is the maximum gloss size per keyword. For last
4213 MD5 hashkeys, Local Cacheing and Global Cacheing(MemCached) enabled number of words are 10 and 40. Corresponding runt
4214 -----
4215 10 words
4216 -----
4217 n=1
4218 d=10
4219 s=constant
4220 tmax=2 (depth 2 recursion)
4221 cpus=2 (dual core)
4222 Runtime = 7 minutes =  $k * 10 * (s)^2 / 2$ 
4223 -----
4224 40 words
4225 -----
4226 n=1
4227 d=40
4228 s=constant
4229 tmax=2 (depth 2 recursion)
4230 cpus=2 (dual core)
4231 Runtime = 28 minutes =  $k * 40 * (s)^2 / 2$ 
4232 Ratio is  $7/28 = k * 10 * (s)^2 / 2 / k * 40 * (s)^2 / 2 = 0.25$  a linear scaling in number of words which substantiates the theoreti
4233
4234 -----
4235 258. (THEORY) Major update to Computational Geometric PRAM-NC algorithm for Discrete Hyperbolic Factorization
4236 -----
4237 PRAM-NC Algorithm for Discrete Hyperbolic Factorization in 34 above:
4238
4239 34.1 LaTeX - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForInteger/
4240 34.2 PDF - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForInteger/
4241
4242 internally relies on [BerkmanSchieberVishkin] and other All Nearest Smaller Values PRAM algorithms for merging sorted
4243
4244 259.1) There are 3 parallel computing models - Parallel Comparisons, Comparator Sorting Networks and PRAMs
4245 259.2) Section 2.4.1 on merging two increasing sequences of length n and m,  $n \leq m$  in Page 19 gives an algorit
4246 259.3) Section 2.4.2 describes Batcher's and [AjtaiKomlosSzmerredi] Bitonic Sort algorithm which sorts n elemen
4247 259.4) Section 2.4.3 describes Cole's PRAM sorting algorithm which requires  $O(\log n)$  steps and  $O(n)$  PRAM proces
4248
4249 Advantage of these older algorithms is they are implementable e.g Bitonic sort - https://en.wikipedia.org/wiki/Bitoni
4250
4251 References:
4252 -----
4253 258.1 Bitonic Sorting - https://cseweb.ucsd.edu/classes/wi13/cse160-a/Lectures/Lec14.pdf
4254
4255 -----
4256 259. Commits as on 10 April 2016
4257 -----
4258 Complement Function script updated with a new function to print Ihara Identity zero imaginary parts mentioned in
4259 Complement Function extended draft:
4260 1. https://sourceforge.net/p/asfer/code/HEAD/tree/asfer-docs/AstroInferDesign.txt
4261 2. https://github.com/shrinivaasanka/asfer-github-code/blob/master/asfer-docs/AstroInferDesign.txt
4262
4263 Logs for this included in python-src/testlogs/
4264
4265 -----
4266 260. Commits (1) as on 12 April 2016
4267 -----
4268 (FEATURE-DONE) Implementation for NC Discrete Hyperbolic Factorization with Bitonic Sort alternative (in lieu of unav
4269

```

```

4270 Bitonic Merge Sort Implementation of:
4271   - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorize
4272   - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorize
4273
4274   - Bitonic Sort is  $O((\log n)^2)$  and theoretically in NC
4275   - Bitonic Sort requires  $O(n^2 \log n)$  parallel comparators. Presently this parallelism is limited to parallel
4276   exchange of variables in bitonic sequence for which python has builtin support (bitonic_compare()) - internally how i
4277   multicore archs is not known.
4278   - a shell script has been added which does the following (cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpper
4279     - NC Factorization implementation with Bitonic Sort is C+++Python (C++ and Python)
4280     - C++ side creates an unsorted mergedtiles array for complete tesselated hyperbolic arc
4281 (cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_Bitonic.cpp)
4282     - This mergedtiles is captured via output redirection and awk in a text file
4283 cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_Bitonic.mergedtiles
4284     - Python bitonic sort implementation which is a modified version of algorithm in https://en.wikipedia.org/wiki/Bitonic\_sort
4285 requires the size of the array to be sorted in exponents of 2. Presently it is hardcoded as array of size 16384 -  $2^{14}$ 
4286 (python-src/DiscreteHyperbolicFactorizationUpperbound_Bitonic.py). It outputs the sorted array. Vacant elements in ar
4287
4288   - Binary and logs for C++ and Python side have been committed
4289   - Parallel comparators on large scale require huge cloud of machines per above bound which makes it NC.
4290 -----
4291 Commits (2) as on 12 April 2016
4292 -----
4293   - Compare step in Bitonic Sort for merged tiles has been Spark MapReduced with this separate script - ../python-src/C
4294
4295 References:
4296 -----
4297 260.1 Parallel Bitonic Sort - http://www.cs.utexas.edu/users/plaxton/c/337/05s/slides/ParallelRecursion-1.pdf
4298
4299 -----
4300 261. Commits as on 13 April 2016
4301 -----
4302 Spark Bitonic Sort - Imported BiDirectional Map - bidict - for reverse lookup (for a value, lookup a key in addition
4303 lookup a value) which is required to avoid the looping through of all keys to match against a tile element.
4304
4305 -----
4306 262. Commits as on 27 April 2016
4307 -----
4308   Interim Commits for ongoing investigation of a race condition in Spark MapReduce for NC Factorization with Bitonic
4309
4310   - The sequential version of bitonic sort has been updated to do away with usage of boolean flag up by 2 compare funct
4311   - Spark NC implementation of Bitonic Sort for Factorization still has some strange behaviour in sorting. In progress
4312 following in Compare-And-Exchange phase:
4313     - Comparator code has been rewritten to just do comparison of parallelized RDD set of tuples where each tuple
4314       (i, i+midpoint)
4315     - This comparison returns a set of boolean flags collect()ed in compare()
4316     - The variable exchange is done sequentially at each local node.
4317     - This is because Spark documentation advises against changing global state in worker nodes (though there are
4318       - There were some unusual JVM out of memory crashes, logs for which have been committed
4319       - some trivial null checks in complement.py
4320       - Bitonic Sort presents one of the most non-trivial cases for parallelism - parallel variable compare-and-exc
4321 and present commits are a result of few weeks of tweaks and trial-errors.
4322     - Still the race condition is observed in merge which would require further commits.
4323
4324 -----
4325 263. Commits as on 28 April 2016
4326 -----
4327 Interim commits 2 for ongoing investigation of race conditions in Spark Bitonic Sort:
4328
4329   - bidict usage has been removed because it requires bidirectional uniqueness, there are better alternatives
4330   - The variable exchange code has been rewritten in a less complicated way and just mimicks what sequential ve
4331 in CompareAndExchange phase.
4332     - logs for Sequential version has been committed
4333     - number to factor has been set to an example low value
4334     - .coordinates and .mergedtiles files have been regenerated
4335     - Still the race condition remains despite being behaviourally similar to sequential version except the paral
4336     - Parallel comparator preserves immutability in local worker nodes
4337
4338 -----
4339 264. (THEORY) UGC(Unique Games Conjecture) and Special Case of Percolation-Majority Voting Circuits
4340
4341 264.1 Unique Games Conjecture by [SubhashKhot] is a conjecture about hardness of approximating certain constraint sat
4342 264.2 Voter Boolean Functions can be written as :
4343   264.2.1 Integer Linear Programs : Voter Judging Boolean Functions are translated into an Integer Linear Progr
4344   264.2.2 and Constraint Satisfaction Problems : Voter expects significant percentage of constraints involving
4345 264.3 Thus RHS of Majority Voting Circuit becomes a functional composition behemoth of indefinite number of individua
4346 264.4 Approximating outcome of a majority voting (e.g. real life pre/post poll surveys) depends thus on following fac
4347   264.4.1 Correctness - Ratio preserving sample - How reflective the sample is to real voting pattern e.g a 60%
4348   264.4.2 Hardness - Approximation of Constraint Satisfaction Problems and UGC.
4349
4350 References:

```



```

4513
4514 Python CAPI interface to NEURONRAIN VIRGO Linux System Calls has been updated to include File System open, read, writ
4515 Rebuilt extension binaries, kern.logs and example appended text file have been committed to testlogs/. This is exactl
4516 commits done for Boost::Python C++ interface. Switch clause has been added to select memory or filesystem VIRGO sysca
4517
4518
4519 278. (FEATURE-DONE) Commits as on 7 June 2016
4520
4521 - getopt implementation for commandline args parsing has been introduced in Maitreya textclient rule search python s
4522 - an example logs for possible high precipitation longitude/latitudes in future dates - July 2016 - predicted by sequ
4523 rules from past data has been added to testlogs/
4524
4525 root@shrinivaasanka-Inspiron-1545:/home/shrinivaasanka/Maitreya7_GitHub/martin-pe/maitreya7/releases/download/v7.1.1/
4526 { --date="2016-7-2 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4527 { --date="2016-7-3 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4528 { --date="2016-7-4 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4529 { --date="2016-7-5 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4530 { --date="2016-7-6 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4531 { --date="2016-7-11 10:10:10 5" --location=" x 77:0:0 7:0:0 " --planet-list } - There is a Class Association Rule m
4532 { --date="2016-7-13 10:10:10 5" --location=" x 77:0:0 7:4:0 " --planet-list } - There is a Class Association Rule m
4533 { --date="2016-7-14 10:10:10 5" --location=" x 77:0:0 7:4:0 " --planet-list } - There is a Class Association Rule m
4534
4535
4536 279. (FEATURE-DONE) Commits - 23 June 2016 - Recurrent Neural Network Long Term Short Term Memory - Deep Learning - I
4537
4538 A very minimal python implementation of LSTM RNN based on Schmidhuber-Hochreiter LSTM has been added to
4539 already existing AsFer algorithms repertoire. LSTM RNN has gained traction in recent years in its variety of
4540 applications in NLP, Speech Recognition, Image Pattern Recognition etc., The logs for this implementation show
4541 a convergence of final output layer in 25th iteration itself (out of 10000). Learning the weights requires
4542 other algorithms like Gradient Descent, Backpropagation (and there are already known limitations in weight learning w
4543
4544
4545 280. (FEATURE-DONE) Commits - 23 June 2016 - Minimal Reinforcement Learning (Monte Carlo Action Policy Search) implem
4546
4547 Reinforcement Learning has been implemented which changes state based on environmental observation and an appropriate
4548 chosen for observation by Monte Carlo Random Policy Search based on which rewards for each transitions are accumulate
4549 Logs for 3 consecutive executions of Reinforcement Learning have been committed with differing total rewards gained.
4550 Input observations are read from text file ReinforcementLearning.input.txt.
4551
4552 Reference: Richard Sutton - http://webdocs.cs.ualberta.ca/~sutton/papers/Sutton-PhD-thesis.pdf
4553
4554
4555 281. (FEATURE-DONE) Commits - 24 June 2016 - ThoughtNet Reinforcement Learning implementation
4556
4557 ThoughtNet based Reinforcement Learning Evocation has been experimentally added as a clause in python-src/DeepLearnin
4558
4559
4560 282. (FEATURE-DONE) Commits - 26 June 2016 - ThoughtNet File System Storage
4561
4562 ThoughtNet text files have been stored into a filesystem backend. It is read and eval()-ed into list of edges and hyp
4563 Separate ThoughtNet directory has been created for these text files.
4564
4565
4566 283. ThoughtNet growth and Evocation Reinforcement Learning algorithm (not feasible to implement exactly):
4567
4568 loop_forever
4569 {
4570 When an observation stimulus from environment arrives:
4571     (*) Sensory instruments that simulate eye, ear, nose, etc., receive stimuli from environment (thoughts, music,
4572 and convert to sentential form - this is of the order of billions - and appended to list in ThoughtNet_Edges.txt
4573     (*) Sentences are classified into categories (for example, by maximum core numbers in definition wordnet subgr
4574     (*) observation is split to atomic units - tokenized - or classified and each unit is lookedup in ThoughtNet_
4575 }
4576
4577
4578 284. (FEATURE-DONE) Auto Regression Moving Average - ARMA - Time Series Analysis for Stock Ticker Stream
4579
4580 Commits - 27 June 2016
4581
4582 1. Time Series Analysis with AutoRegressionMovingAverage of Stock Quote streamed data has been implemented (R functic
4583 show the actual data and projected quotes by ARMA for few iterations have been committed to testlogs. This ARMA proje
4584 2. ARMA code implements a very basic regression+moving averages. Equation used is same though not in usual ARMA forma
4585 (1-sigma())X(t) = (1+sigma())
4586 3. Also committed is the R plot for SequenceMined Pattern in first 10000 prime numbers in binary format (DJIA approx
4587
4588
4589 285. (FEATURE-DONE) Commits 1 - 28 June 2016 - Neo4j ThoughtNet Hypergraph Database Creation
4590
4591 1.New file ThoughtNet_Neo4j.py has been added to repository which reads the ThoughtNet edges and hypergraph text file
4592 Neo4j Graph Database through py2neo client for Neo4j.
4593 2.Neo4j being a NoSQL graph database assists in querying the thoughtnet and scalable.

```

4594 3.ThoughtNet text files have been updated with few more edges and logs for how Neo4j graph database for ThoughtNet lc
4595 committed to testlogs/

4596

4597 -----
4598 286. (FEATURE-DONE) Commits 2 - 28 June 2016 - ThoughtNet Neo4j Transactional graph creation
4599 -----
4600 1.transactional begin() and commit() for graph node and edges creation has been
4601 included.
4602 2.This requires disabling bolt and neokit disable-auth due to an auth failure config issue.
4603 3.Logs and a screenshot for the ThoughtNet Hypergraph created in GUI (<http://localhost:7474>) have been committed to t
4604 -----
4605 287. (FEATURE-DONE) Commits - 29 June 2016 - ThoughtNet and Reinforcement Deep Learning
4606 -----
4607 Major commits for ThoughtNet Hypergraph Construction and Reinforcement Learning from it
4608 -----
4609 1. python-src/DeepLearning_ReinforcementLearningMonteCarlo.py reads from automatically generated ThoughtNet Hypergraph
4610 by python-src/ThoughtNet/Create_ThoughtNet_Hypergraph.py in python-src/ThoughtNet/ThoughtNet_Hypergraph_Generated.txt
4611 2. Separate Recursive Gloss Overlap CoreNumber and PageRank based Unsupervised Classifier has been implemented in pyt
4612 3. python-src/ThoughtNet/ThoughtNet_Neo4j.py reads from automatically generated ThoughtNet in python-src/ThoughtNet/T
4613 4. Logs for above have been committed to respective testlogs/ directories
4614 5. Compared to human evaluated ThoughtNet Hypergraphs in python-src/ThoughtNet/ThoughtNet_Hypergraph.txt, generated p
4615 6. python-src/ReinforcementLearning.input.txt and python-src/ThoughtNet/ThoughtNet_Edges.txt have been updated manual
4616 -----
4617 288. (FEATURE-DONE) Schematic Diagram for ThoughtNet Reinforcement Evocation - approximate implementation of 283
4618 -----
4619

4620

4621

4622 Environment -----(stimuli)-----> Sensors -----> Create_ThoughtNet_Hypergraph.py -----> RecursiveGlossOverla
4623 |
4624 V
4625 |
4626 V
4627 Observations-----> DeepLearning_ReinforcementLearningMonteCarlo.py -----> Evoc
4628 -----
4629 289. (FEATURE-DONE) Commits - 30 June 2016 - Sentiment Scoring of ThoughtNet edges and Sorting per Class
4630 -----
4631 1. Create_ThoughtNet_Hypergraph.py has been changed to do sentiment scoring which is a net of positivity, negativity
4632 thought hyperedge and to sort the per-class key list of hyperedges descending based on sentiment scores computed.
4633 2. python-src/ReinforcementLearning.input.txt which is the input observation stimulus and python-src/ThoughtNet/Thoug
4634 3. Hypergraph created for this is committed at python-src/ThoughtNet/ThoughtNet_Hypergraph_Generated.txt with logs in
4635 -----
4636 This completes ThoughtNet Classifications based Evocative Inference implementation minimally.
4637 -----
4638 290. (FEATURE-DONE) Commits - 1 July 2016 - Reinforcement Learning Bifurcation
4639 -----
4640 Reinforcement Learning code has been bifurcated into two files than having in if-else clause, for facilitating future
4641 one for MonteCarlo and the other for ThoughtNet Evocation. Logs for these two have been committed to testlogs.
4642 -----
4643 291. (THEORY) Logical Time and ThoughtNet (related to EventNet 70-79)
4644 -----
4645 ThoughtNet Hypergraph is multiplanar and when seen from elevation it resembles billions of skyscraper category towers
4646 HyperEdges which are classified onto these categories. This gives an alternative route to define Time. Each tower rep
4647 -----
4648 As a working example, following edges were evoked when word "economic" was uttered:
4649 ======
4650 Observation: economic
4651 evocative thought (reward) returned(in descending order of evocation potential): The HDI was created to emphasize the
4652 evocative thought (reward) returned(in descending order of evocation potential): We need an SPI and we need to unders
4653 evocative thought (reward) returned(in descending order of evocation potential): Social progress depends on the polic
4654 ======
4655 Only the top most evocative edge (sorted based on sentiment scores) has the word "economics" in it while the other tw
4656 -----
4657 A practical ThoughtNet storage could be of billions of edges based on experiential learning of an individual over a p
4658 - Word: Sensory receptors perceive stimuli - events
4659 - Mind: stimuli evoke thoughts in past
4660 - Action: Evocative thought is processed by intellect and inspires action - action is a lambda evaluation of
4661 #####
4662 Senses(Word) <-----> Mind(Evocation) <-----> Action(Intellect)
4663 ^ ^
4664 |<----->|
4665 and above is an infinite cycle. Previous schematic maps interestingly to Reinforcement Learning(Agent-Environment-Act
4666 #####
4667 In this aspect, ThoughtNet is a qualitative experimental inference model compared to quantitative Neural Networks.
4668 -----
4669 -----
4670 -----
4671 -----
4672 -----
4673 -----
4674 -----

4675 It is assumed in present implementation that every thought edge is a state implicitly, and the action
 4676 for the state is the "meaning" inferred by recursive lambda evaluation (lambda composition tree evaluation for a natu
 4677 language sentence is not implemented separately because its reverse is already done through closure of a RGO graph in
 4678 code in NeuronRain AsFer. Approximately every edge in Recursive Gloss Overlap wordnet subgraph is a lambda function w
 4679 two vertices as operands which gives a more generic lambda graph composition of a text)

4681 -----
 4682 292. (THEORY) Recursive Lambda Function Growth Algorithm and Recursive Gloss Overlap Graph - 216 Continued
 4683 -----
 4684 Lambda Function Recursive Growth algorithm for inferring meaning of natural language text approximately, mentioned in
 4685 on creation of lambda function composition tree top-down by parsing the connectives and keywords of the text. Alterna
 4686 parsing is to construct the lambda function composition graph instead from the Recursive Gloss Overlap WordNet subgra
 4687 each edge is a lambda function with two vertex endpoints as operands (mentioned in 291). Depth First Traversal of thi
 4688 evaluates a lambda function f_1 of an edge, f_1 is applied to next edge vertices in traversal to return $f_2(f_1)$, and so
 4689 $f_n(f_{n-1}(f_{n-2}(\dots(f_2(f_1))\dots))$ which completes the recursive composition. Which one is better - tree or graph lambda
 4690 on the depth of learning necessary. Rationale in both is that the "meaning" is accumulated left-right and top-down or
 4691 -----
 4692 293. (FEATURE-DONE) Commits - 7 July 2016 - Experimental implementation of Recursive Lambda Function Growth Algorithm
 4693 -----
 4694 1. Each Sentence Text is converted to an AVL Balanced Tree (inorder traversal of this tree creates the original text)
 4695 2. Postorder traversal of this tree computes a postfix expression
 4696 3. Postfix expression is evaluated and a lambda function composition is generated by parenthesization denoting a funct
 4697 for this have been committed to testlogs/ which show the inorder and postorder traversal and the final lambda functio
 4698 4. This is different from Part of Speech tree or a Context Free Grammar parse tree.
 4699 5. On an average every english sentence has a connective on every third word which is exactly what inorder traversal c
 4700 -----
 4701 294. (FEATURE-DONE) Commits - 8 July 2016
 4702 -----
 4703 Changed Postfix Evaluation to Infix evaluation in Lambda Function Growth with logs in testlogs/
 4704 -----
 4705 295. (THEORY) Contextual Multi-Armed Bandits, Reinforcement Learning and ThoughtNet - related to 241, 291, 292 - 18 J
 4706 -----
 4707 Contextual Multi-Armed Bandits are the class of problems where a choice has to be made amongst k arms and each iterat
 4708 -----
 4709 Reference:
 4710 -----
 4711 295.1 Multiword Testing Decision Service - <http://arxiv.org/pdf/1606.03966v1.pdf>
 4712 -----
 4713 296. (FEATURE-DONE) Music Pattern Mining - Jensen-Shannon Divergence Distance between two FFT Frequency Distributions
 4714 -----
 4715 Commits - 20 July 2016 - related to 68, 69
 4716 -----
 4717 (NOTE: Because of some weird SourceForge/GitHub error, FFT txt files added to repos on 19 July 2016 are still flagged
 4718 added to repos again along with new files)
 4719 -----
 4720 FFTs of 2 audio files are parsed and written to *_trimmed.txt by awk to contain only the frequencies for each sample.
 4721 These files are read by JensenShannonDivergence.py to compute the JS Distance between these two FFT frequency distri
 4722 Preprocessing is done so as to normalize the frequency to map to a probability (frequency/sum_of_frequencies) which g
 4723 probability distribution from frequency distribution. Jensen-Shannon Distance which is the weighted average of bidire
 4724 Kullback-Leibler Divergence measures of the two distributions, indicates similarity or distance between two music sam
 4725 quantitatively.
 4726 -----
 4727 There are 4 music samples: music_pattern_mining/FFT_classical_1_20July2016.txt and music_pattern_mining/FFT_classical
 4728 are similar (similar notes sung by different musicians). music_pattern_mining/FFT_classical_1_19July2016.txt and
 4729 music_pattern_mining/FFT_classical_2_19July2016.txt are also similar (different set of notes sung by different musici
 4730 distance across these 4 ordered pairs is captured and committed in testlogs/
 4731 -----
 4732 Jensen-Shannon Distance across 2 FFT Frquency-Probability distributions of music samples is a simple, basic measure f
 4733 basis for clustering and classification of music. There could be some inaccuracies because Audacity does not generate
 4734 music file but only for first ~5 minutes. Two similar notes with different musicians could be distant and two dissimi
 4735 close because of this Audacity limitation. Presently noise filtering and cherrypick peak frequencies is not done and
 4736 entire frequency range is compared.
 4737 -----
 4738 297. (FEATURE-DONE) Software Analytics - Cyclomatic Complexity from SATURN .dot graphs - related to 65
 4739 -----
 4740 Commits - 22 July 2016
 4741 -----
 4742 New Python-Spark implementation that reads the SATURN program analyzer generated .dot graph files processes them with
 4743 MapReduce to find the number of edges and vertices in the graph represented by .dot file for each snippet. From this
 4744 Cyclomatic Complexity is calculated (which is Edges - Vertices + 2) - a standard Function Point Estimator for code c
 4745 There were some JVM crashes frequently while starting up spark-submit logs for which are also committed in testlogs a
 4746 the two successful Spark computed Cyclomatic Complexity measures for two .dot files. These .dot files are sourced fr
 4747 VIRGO Linux saturn program analysis kernel driver.
 4748 -----
 4749 298. (FEATURE-DONE) String Search - Longest Common Substring - Suffix Trees(Suffix Arrays+LCP) Implementation

4756
 4757 Commits - 26 July 2016
 4758
 4759 This implementation finds the most repeated substrings within a larger string by constructing Suffix Trees
 4760 indirectly with Suffix Array and Longest Common Prefix (LCP) datastructures. An ideal application for String Search i
 4761 in Bioinformatics, Streamed Data analysis etc., For example, a Time Series data with fluctuating curve can be
 4762 encoded as a huge binary string by mapping ebb and tide to 0 and 1. Thus a function graph time series is projected on
 4763 {0,1} alphabet to create blob. Usual Time Series analysis mines for Trends, Cycles, Seasons and Irregularities over t
 4764 This binary encoding of time series gives an alternative spectacle to look at the trends (highs and lows). Longest re
 4765 pattern in this binary encoding is a cycle. Suffix Array by [UdiManber] has been implemented over Suffix Trees implem
 4766 of [Weiner] and [Ukkonen] because of simplicity of Suffix Arrays and Suffix Trees=Suffix Arrays + LCPs.
 4767
 4768 299. (FEATURE-DONE) Binary String Encoding of Time Series - Commits - 27 July 2016
 4769
 4770 1. New python script to encode a time series datastream as binary string has been added to repository.
 4771 2. This writes to StringSearch_Pattern.txt which is read by StringSearch_LongestRepeatedSubstring.py
 4772 3. Encoding scheme: If next data point is smaller, write 0 else if greater write 1. This captures the
 4773 fluctuations in dataset irrespective of the amplitudes at each point.
 4774 4. For example a bitonic sequence would have been encoded as11111110000000.... (ascends and descends)
 4775 5. Suffix Array + LCP algorithm on this sequence finds the Longest Repeated Substring. For a specific example of
 4776 Stock ticker time series data this amounts to frequently recurring fluctuation pattern.
 4777 6. Logs for the above have been committed to testlogs/
 4778 7. Every time series dataset is a union of bitonic sequences with varying lengths corresponding to peaks and troughs
 4779 and has self-similar fractal structure (zooming out the series has similarities to original series) . This implies th
 4780 binary string encoded as previously is fractal too.
 4781
 4782 300. (FEATURE-DONE) Tornado GUI Authentication Template - Commits - 27 July 2016
 4783
 4784 Rewritten Tornado GUI with Login Template and redirect to Algorithms Execution Template. Presently implemented for or
 4785 root user by cookie setting. Entry point has been changed to http://host:33333/neuronrain_auth (Login).
 4786
 4787 301. (FEATURE-DONE) OAuth2 authentication and credentials storage in MongoDB/Redis with passlib sha256 encryption
 4788
 4789 1.Login Handler has been augmented with OAuth2 authentication by python-oauth2 library.
 4790 2.MongoDB is used as OAuth2 credentials storage backend and Redis for token storage backend
 4791 3.Passlib is used to encrypt the password with SHA256 hash digest and stored once in MongoDB (code is commented)
 4792 4.Login page password is verified with passlib generated hash in MongoDB queried for a username argument
 4793 5.With this minimal standard authentication has been implemented for NeuronRain cloud deployment.
 4794 6.Prerequisite is to populate MongoDB neuronrain_oauth database and neuronrain_users collections with
 4795 passlib encrypted JSON by uncommenting the collections.insert_one() code.
 4796
 4797 302. Commits - 29 July 2016 - boost::python extensions for VIRGO Linux Kernel system calls
 4798
 4799 virgo_clone() system call has been included in switch-case and invokes an exported kernel module function in kernelsp
 4800
 4801 303. (THEORY) Update on Bitonic Sort Merge Tree for Discrete Hyperbolic Factorization Spark Cloud Implementation in 3
 4802
 4803 Bitonic Sort Merge Tree for Discrete Hyperbolic Factorization described in <http://sourceforge.net/projects/acadpdraft>
 4804
 4805 303.1 Bitonic Sort requires $O((\log N)^2)$ time with $O(N * (\log N)^2)$ processors.
 4806 303.2 Discretized Hyperbolic arc of length N can be split into $N/\log N$ segments of length $\log N$ each.
 4807 303.3 Above $N/\log N$ segments can be grouped in leaf level of merge tree into $N/2\log N$ pairs of $(\log N, \log N) = 2\log N$ leng
 4808 303.4 Each such pair can be sorted in $\log(2\log N)$ time in parallel with $N/(2\log N) * N(\log N)^2 = N^2/2\log N$ comparator p
 4809 303.5 Height of the merge tree is $O(\log(N/\log N))$. Total sort time is sum over sorts at each level of merge tree = \log
 4810 303.6 Total sort time of merge tree is upperbounded as (not tight one) height * maximum_sort_time_per_level:
 4811 $\leq O(\log(N/\log N) * \log(N/\log N * \log N)) = O(\log(N/\log N) * \log(N))$
 4812 with maximum of $N^2/2\log N$ processor comparators at leaf which tapers down up the tree.
 4813 303.7 Binary Search on final sorted merged tile requires additional $O(\log N)$ which effectively reduces to:
 4814 $O(\log(N/\log N) * \log N + \log N) = O(\log(N/\log N) * \log N) \leq O((\log N)^2)$ time
 4815 with $N^2/2\log N$ processor comparators for finding a factor.
 4816 303.8 This is comparably better bound than the Parallel RAM ANSV algorithm based merge sort alternatives and easy to
 4817 303.9 Again the input size is N and not $\log N$, but yet definition of NC is abided by. It remains an open question whet
 4818
 4819 304. Commits - 31 July 2016 - boost::python C++ and cpython virgo_clone() system call invocations
 4820
 4821 1. Boost C++ Python extensions - virgo_clone() system call has been included in switch-case for cpython invocation of
 4822 2. CPython extensions - test log for boost::python virgo_clone() invocation with use_as_kingcobra_service=0 which dir
 4823
 4824 305. NEURONRAIN VIRGO Commits for ASFER Boost::Python C++ virgo memory system calls invocations
 4825
 4826 (BUG - STABILITY ISSUES) Commits - 1 August 2016 - VIRGO Linux Stability Issues - Ongoing Random oops and panics inve
 4827
 4828 1. GFP_KERNEL has been replaced with GFP_ATOMIC flags in kmem allocations.
 4829 2. NULL checks have been introduced in lot of places involving strcpy, strcat, strcmp etc., to circumvent

```

4837 buffer overflows.
4838 3. Though this has stabilized the driver to some extent, still there are OOPS in unrelated places deep
4839 with in kernel where paging datastructures are accessed - kmalloc somehow corrupts paging
4840 4. OOPS are debugged via gdb as:
4841     4.1 gdb ./vmlinux /proc/kcore
4842     or
4843     4.2 gdb <loadable_kernel_module>.o
4844 followed by
4845     4.3 l *(address+offset in OOPS dump)
4846 5. kern.log(s) for the above have been committed in tar.gz format and have numerous OOPS occurred during repetitive t
4847 invocation(boost::python C++) invocations of virgo memory system calls.
4848 6. Paging related OOPS look like an offshoot of set_fs() encompassing the filp_open VFS calls.
4849 7. In C++ Boost::Python extensions, flag changed for VIRGO memory system calls invocation from python.

-----
4851 306. Commits - 3 August 2016
4852 -----
4853 Social Network Analysis with Twitter - Changes to Belief Propagation Potential Computation
4854 -----
4855 1. Exception handling for UnicodeError has been added in SentimentAnalyzer
4856 2. Belief Propagation Potential computation for the RG0 graph constructed has been changed to do plain
4857 summation of positivity and negativity scores for DFS of K-Core rather than multiplication which heuristically
4858 appears to predict sentiments better
4859 3. An example for tweets sentiments analysis for 2 search keywords has been logged and committed in testlogs/
4860 -----
4861 4. Excerpts for sentiment scores - positive and negative - from RG0 graph of few tweets
4862 -----
4863 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4864 K-Core DFS belief_propagated_posscore: 6.078125
4865 K-Core DFS belief_propagated_negscore: 8.140625
4866 Core Number belief_propagated_posscore: 25.125
4867 Core Number belief_propagated_negscore: 26.125
4868 K-Core DFS belief_propagated_posscore: 6.078125
4869 K-Core DFS belief_propagated_negscore: 8.140625
4870 Core Number belief_propagated_posscore: 25.125
4871 Core Number belief_propagated_negscore: 26.125
4872 K-Core DFS belief_propagated_posscore: 55.09375
4873 K-Core DFS belief_propagated_negscore: 54.3125
4874 Core Number belief_propagated_posscore: 92.625
4875 Core Number belief_propagated_negscore: 93.875
4876 K-Core DFS belief_propagated_posscore: 60.09375
4877 K-Core DFS belief_propagated_negscore: 59.3125
4878 Core Number belief_propagated_posscore: 118.625
4879 Core Number belief_propagated_negscore: 117.75
4880 root@shrinivaasanka-Inspiron-1545:/media/shrinivaasanka/0fc4d8a2-1c74-42b8-8099-9ef78d8c8ea2/home/kashrinivaasan/Kris
4881 K-Core DFS belief_propagated_posscore: 34.0
4882 K-Core DFS belief_propagated_negscore: 30.359375
4883 Core Number belief_propagated_posscore: 90.25
4884 Core Number belief_propagated_negscore: 85.125
4885 K-Core DFS belief_propagated_posscore: 54.0
4886 K-Core DFS belief_propagated_negscore: 46.734375
4887 Core Number belief_propagated_posscore: 111.125
4888 Core Number belief_propagated_negscore: 108.125
4889 K-Core DFS belief_propagated_posscore: 97.203125
4890 K-Core DFS belief_propagated_negscore: 91.015625
4891 Core Number belief_propagated_posscore: 172.125
4892 Core Number belief_propagated_negscore: 172.125
4893 K-Core DFS belief_propagated_posscore: 97.203125
4894 K-Core DFS belief_propagated_negscore: 91.015625
4895 Core Number belief_propagated_posscore: 178.125
4896 Core Number belief_propagated_negscore: 178.125
4897
4898 5. Majority Predominant Sentiment indicated by above scores for randomly sampled tweets can be used as one of the Ele
4899 -----
4900 -----
4901 307. (THEORY) Sentiment Analysis from Recursive Gloss Overlap as a Voting Function in Majority Voting - related to 14
4902 -----
4903 As mentioned in 306, Sentiment Analysis scores derived from Recursive Gloss Overlap graph of a text is an indirect vc
4904 overall sentiment is negative it is an "against" vote and when positive it is a "for" vote. In this sense, Sentiment
4905 -----
4906 -----
4907 308. (FEATURE-DONE) Markov Random Fields (MRF) Belief Propagation - Commits - 8 August 2016
4908 -----
4909 Existing Sentiment Analyzer does belief propagation by computing product of potentials in DFS traversal only.
4910 New function for Markov Random Fields Belief Propagation has been included which handles the generalized case of beli
4911 graph by factoring it into maximal cliques and finding potentials per clique. These per clique potentials are multipl
4912 with number of cliques to get polarized sentiments scores - positive, negative and objective. Logs for Sentiment Anal
4913 with MRF have been committed to testlogs/
4914 -----
4915 -----
4916 Reference:
4917 -----

```

4918 308.1 Introduction to Machine Learning - [Ethem Alpaydin] - Graphical Models
 4919
 4920
 4921 309. (FEATURE-DONE) Commits - 12 August 2016 - Boost 1.58.0 upgrade from 1.55.0 - Boost::Python C++ extensions for VI
 4922
 4923 1.Rebuilt Boost::Python extensions for VIRGO Linux kernel system calls with boost 1.58 upgraded from boost 1.55.
 4924 2.kern.log for miscellaneous VIRGO system calls from both telnet and system call request routes has been compressed a
 4925 testlogs (~300MB).
 4926 Following multiple debug options were tried out for heisenbug resolution (Note to self):
 4927 3./etc/sysctl.conf has been updated with kernel panic tunables with which the mean time between crashes has increased
 4928 deep within kernel (VMA paging) - commits for this are in VIRGO linux tree. With these settings following usecase wor
 4929 virgo_cloud_malloc()
 4930 virgo_cloud_set()
 4931 virgo_cloud_get()
 4932 virgo_cloud_set() overwrite
 4933 virgo_cloud_get()
 4934 through telnet route.
 4935 4.Debugging VIRGO linux kernel with an Oracle VirtualBox virtual machine installation and debugging the VM with a net
 4936 5.Debugging VIRGO linux kernel with QEMU-KVM installation and debugging the VM with a netconsole port via KGDB is bei
 4937 6.Path to boost::python extension .so has been updated.

4938
 4939
 4940 310. (THEORY) DFT of a Sliding Window Fragment of Time Series, Integer Partitions and Hashing
 4941
 4942 Time Series Data Stream can be viewed through a sliding window of some fixed width moving across the data. Captured data
 4943 window are analyzed in frequency domain with a Discrete Fourier Transform. If there are n frequencies in the window can
 4944 sinusoids which superimpose to form the original data. In discrete sense, sinusoids partition the data at any time point
 4945 relation between hash functions and integer partitions in <https://sites.google.com/site/kuja27/IntegerPartitionAndHashing>
 4946 each of n discrete sinusoid in DFT corresponds to a hash function and the time-series sliding window is an amalgamation
 4947
 4948
 4949 311. (THEORY) Pr(Good) Majority Voting Circuit, Percolation, PRG choice and Boolean Circuit Composition - related to
 4950
 4951 Even though Percolation circuit is in Noise Stability Regime with zero sensitivity and 100% stability, delta term merging
 4952 of 14 and 53 (second column) need not be zero which could force percolation circuit to be in BPNC. Problem is then de
 4953
 4954 References:
 4955
 4956 311.1 Mathematical Techniques for Analysis of Boolean Functions - [AnnaBernaconi] - 2.8.2 Boolean Function Compositi
 4957 311.2 Properties and Applications of Boolean Function Composition - [AvishayTal] - eccc.hpi-web.de/report/2012/163/dc
 4958 311.3 Boolean Circuit Composition - www.cs.tau.ac.il/~safra/ACT/CCAndSpaceB.ppt
 4959
 4960
 4961 312. (THEORY) Circuit SAT lowerbounds for Pr(Good) Majority Voting - related 14 and 129
 4962
 4963 312.1 RHS of Pr(Good) Majority Voting circuit is an NC circuit in composition with CircuitSAT for each voter. This part
 4964 requires some kind of barrier synchronization so that input from all voters is available to NC Majority Circuit. This needs to be ignored because the barrier delay depends on the voter whose decision time is the most. If in worst case the barrier is in EXP then barrier synchronization is also in EXP. It is also assumed that voters decide independent of each other.
 4965 312.2 CircuitSAT is the circuit version of CNF SAT concerned with the bounds for finding satisfying assignments to a
 4966 312.3 An arbitrary Circuit's Satisfiability requires $O(2^{\lceil 0.4058m \rceil})$ where m is the number of gates in Circuit(i.e. size
 4967 312.4 Because of the fact that Pr(good) majority voting is a circuit composition with voter circuit SATs as inputs to
 4968 312.5 Let number of voters be n and number of gates on the average per voter be m. NC1 majority requires $O(\log n)$ time
 4969 312.6 If number of voters is exponential in number of gates per voter then $n=2^m$ which is the worst case scenario and
 4970 312.7 In a very generic case, as mentioned in 275, each voter can have a non-boolean voting function viz., a linear function
 4971 312.7.1 NC^P (if voting functions are real LP) and LHS NC/poly or BPNC percolation lowerbounds NC^P when both
 4972 312.7.2 NC^{NP} (if voting functions are integer LP) and LHS NC/poly or BPNC percolation lowerbounds NC^{NP} when
 4973 312.8 Circuit Size of Pr(Good) RHS is non-trivial to determine. All that is known so far is the bound for CircuitSAT
 4974 312.9 Assumption 1: Each voter has different variables - set of variables of voters are all pairwise disjoint.
 4975 312.10 If number of voters is arbitrarily huge and if number of voters is exponential in number of gates per voter SAT
 4976 312.11 Even if m (number of gates per voter SAT) is assumed to be polynomial in number of input variables i.e. $m=f(v)$
 4977 312.12 If both LHS and RHS of Pr(Good) are of zero or equal error, LHS lowerbounds RHS (an assumption made throughout
 4978 312.13 Important notion in representing a voter boolean function by a circuit is Hardness which is defined as:
 4979 A boolean function $f:\{0,1\}^n \rightarrow \{0,1\}$ is h-hard if there exists a circuit C of size s such that for all x in $\{0,1\}^n$, $F(x) = f(x)$
 4980 312.14 There are two classes of errors: Voter error + Voting error. Voter error is the Noise Sensitivity of a voter to
 4981
 4982 References:
 4983
 4984 312.15 Complexity Hardness of Noisy Boolean Functions - <http://cstheory.stackexchange.com/questions/18822/hardness-of-noisy-boolean-functions>
 4985 312.16 Hardness of Boolean Functions and Amplification - [RyanODonnell] - <https://www.cs.cmu.edu/~odonnell/boolean-analysis.pdf>
 4986 312.17 Probabilistic Boolean Logic - [LakshmiNBChakrapani-KrishnaPalem] - <http://www.ece.rice.edu/~al4/visen/2008rice.pdf>
 4987 312.18 How much a Linear Programming Oracle speeds up Polytime algorithms - <http://cstheory.stackexchange.com/questions/18822/hardness-of-noisy-boolean-functions>
 4988 312.19 Algorithms for Circuits and Circuits for Algorithms - [RyanWilliams] - <http://web.stanford.edu/~rrwill/ICM-surv.pdf>
 4989 312.20 Depth 3 multilinear circuits - [OdedGoldreich] - <http://www.wisdom.weizmann.ac.il/~oded/R3/kk.pdf> - D-canonical
 4990 312.21 Size hierarchy theorem for circuits - <http://cstheory.stackexchange.com/questions/5110/hierarchy-theorem-for-circuits>
 4991 312.22 Size Hierarchy [Lupanov] - Number of functions computable by circuit of size s - Lemma 2.1 counting argument -
 4992 312.23 Efficient Parallel Computation = NC - [AroraBarak] - <http://theory.cs.princeton.edu/complexity/book.pdf> - Theorem 1.1
 4993 312.24 Size hierarchy of 312.22 in Pr(Good) majority voting circuit context implies that number of functions computable
 4994 312.25 If circuit sizes differ in zero-error case on both sides i.e. when 100% convergence occurs (or) equal error on
 4995 312.26 There is an alternative definition of Boolean function hardness in <http://www.math.ias.edu/~avi/PUBLICATIONS/1998.html>


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5404 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:0:0 " --planet-list } - There is a Class Association Rule
5405 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:0:0 " --planet-list } - There is a Class Association Rule
5406 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:1:0 " --planet-list } - There is a Class Association Rule
5407 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:1:0 " --planet-list } - There is a Class Association Rule
5408 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:1:0 " --planet-list } - There is a Class Association Rule
5409 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:1:0 " --planet-list } - There is a Class Association Rule
5410 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:2:0 " --planet-list } - There is a Class Association Rule
5411 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:2:0 " --planet-list } - There is a Class Association Rule
5412 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:2:0 " --planet-list } - There is a Class Association Rule
5413 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:2:0 " --planet-list } - There is a Class Association Rule
5414 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:3:0 " --planet-list } - There is a Class Association Rule
5415 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:3:0 " --planet-list } - There is a Class Association Rule
5416 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:3:0 " --planet-list } - There is a Class Association Rule
5417 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:3:0 " --planet-list } - There is a Class Association Rule
5418 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:4:0 " --planet-list } - There is a Class Association Rule
5419 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:4:0 " --planet-list } - There is a Class Association Rule
5420 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:4:0 " --planet-list } - There is a Class Association Rule
5421 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:4:0 " --planet-list } - There is a Class Association Rule
5422 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:5:0 " --planet-list } - There is a Class Association Rule
5423 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:5:0 " --planet-list } - There is a Class Association Rule
5424 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:5:0 " --planet-list } - There is a Class Association Rule
5425 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:5:0 " --planet-list } - There is a Class Association Rule
5426 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:6:0 " --planet-list } - There is a Class Association Rule
5427 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:6:0 " --planet-list } - There is a Class Association Rule
5428 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:6:0 " --planet-list } - There is a Class Association Rule
5429 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:6:0 " --planet-list } - There is a Class Association Rule
5430 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:7:0 " --planet-list } - There is a Class Association Rule
5431 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:7:0 " --planet-list } - There is a Class Association Rule
5432 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:7:0 " --planet-list } - There is a Class Association Rule
5433 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:7:0 " --planet-list } - There is a Class Association Rule
5434 { --date="2016-11-29 10:10:10 5.5" --location=" x 77:3:0 9:8:0 " --planet-list } - There is a Class Association Rule
5435 { --date="2016-11-30 10:10:10 5.5" --location=" x 77:3:0 9:8:0 " --planet-list } - There is a Class Association Rule
5436 { --date="2016-12-1 10:10:10 5.5" --location=" x 77:3:0 9:8:0 " --planet-list } - There is a Class Association Rule
5437 { --date="2016-12-2 10:10:10 5.5" --location=" x 77:3:0 9:8:0 " --planet-list } - There is a Class Association Rule
5438 { --date="2016-11-29 10:10:10 5" --location=" x 77:4:0 7:0:0 " --planet-list } - There is a Class Association Rule
5439 { --date="2016-11-30 10:10:10 5" --location=" x 77:4:0 7:0:0 " --planet-list } - There is a Class Association Rule
5440 { --date="2016-12-1 10:10:10 5" --location=" x 77:4:0 7:0:0 " --planet-list } - There is a Class Association Rule
5441 { --date="2016-12-2 10:10:10 5" --location=" x 77:4:0 7:0:0 " --planet-list } - There is a Class Association Rule
5442 { --date="2016-11-29 10:10:10 5" --location=" x 77:4:0 7:1:0 " --planet-list } - There is a Class Association Rule
5443 { --date="2016-11-30 10:10:10 5" --location=" x 77:4:0 7:1:0 " --planet-list } - There is a Class Association Rule
5444 { --date="2016-12-1 10:10:10 5" --location=" x 77:4:0 7:1:0 " --planet-list } - There is a Class Association Rule
5445 { --date="2016-12-2 10:10:10 5" --location=" x 77:4:0 7:1:0 " --planet-list } - There is a Class Association Rule
5446 { --date="2016-11-29 10:10:10 5" --location=" x 77:4:0 7:2:0 " --planet-list } - There is a Class Association Rule
5447 { --date="2016-11-30 10:10:10 5" --location=" x 77:4:0 7:2:0 " --planet-list } - There is a Class Association Rule
5448 { --date="2016-12-1 10:10:10 5" --location=" x 77:4:0 7:2:0 " --planet-list } - There is a Class Association Rule
5449 { --date="2016-12-2 10:10:10 5" --location=" x 77:4:0 7:2:0 " --planet-list } - There is a Class Association Rule
5450
5451 -----
5452 314. (THEORY) Pseudorandomness, Voter Decision Error and lambda-tolerant Randomized Decision Trees of Voter Boolean F
5453 -----
5454 Pseudorandom generators are those which stretch a seed  $l(n)$  to  $n : f:\{0,1\}^l(n) \rightarrow \{0,1\}^n$  indistinguishable from perfectly random with bounded error. References 314.1 and 314.2 describe a counting argument to show that there are PRGs. For a seed  $l$ 
5455
5456 References:
5457 -----
5458 314.1 Definition of Pseudorandomness - Simpler Distinguisher - http://people.seas.harvard.edu/~salil/pseudorandomness
5459 314.2 Definition of Pseudorandomness - Counting argument - http://www.cse.iitk.ac.in/users/manindra/survey/complexity
5460 314.3 Lambda-tolerant Randomized Boolean Decision Trees - https://www.math.u-szeged.hu/~hajnal/research/papers/dec\_si
5461
5462 -----
5463 315. (FEATURE-DONE and BUG-STABILITY ISSUES) NeuronRain AsFer Commits for Virgo Linux - Commits - 25 August 2016
5464 -----
5465 Kernel Panic investigation for boost::python c++ invocations of Virgo System Calls
5466
5467 1.Python code in AsFer that invokes Virgo Linux system calls by boost::python C++ bindings is being investigated further
5468 2.kern.log with 3 iterations of virgo_malloc() + virgo_set() + virgo_get() invocations succeeded by panics in random order
5469 3.Logs also contain the gdb vmlinux debugging showing line numbers within kernel source where panics occur. Prima facie
5470
5471 -----
5472 316. (FEATURE-DONE and BUG-STABILITY ISSUES) NeuronRain AsFer Commits for Virgo Linux - Commits - 26 August 2016
5473 -----
5474 Kernel Panic investigation for boost::python c++ invocations of Virgo System Calls
5475
5476 -----
5477 kern.log with panic in FS code after boost::python C++ AsFer-VIRGO Linux system calls invocations
5478
5479 -----
5480 317. (THEORY) Generic Definitions of Majority and Non-majority Choice Errors and some contradictions - related to 14
5481
5482 Majority Voting Social Choice has usual meaning of aggregation of for and against votes. Non-majority Social Choice can have multiple flavours:
5483
5484 317.1 Pseudorandom Choice - a Pseudorandom Generator chooses a voting function from a set of Voting functions

```

5485 317.2 Social choice by ranking - set of boolean functions are ranked ascending in their error probabilities ar
 5486
 5487
 5488 Algorithm for 317.1:
 5489
 5490 There are pseudorandom generators in NC(Applebaum PRG, Parallel PRGs etc.,) which choose a boolean function at random
 5491 - Invoke a PRG in NC or P to obtain pseudorandom bits X.
 5492 - Choose an element in electorate indexed by X.
 5493 - Goodness of LHS is equal to the goodness of chosen element.
 5494
 5495 LHS is BPNC algorithm to RHS BPEXP Condorcet Jury Theorem (CJT) unbounded circuit and if CJT converges to 1 in RHS ar
 5496
 5497 Algorithm for 317.2:
 5498
 5499 - foreach(voter)
 5500 - {
 5501 - Interview the voter boolean function : Rank the voters by merit (error probabilities e.g noise stabili
 5502 - }
 5503 - choose the topmost as non-majority social choice
 5504
 5505 LHS is a PSPACE-complete algorithm and RHS is either BPEXP or EXP algorithm depending on convergence or divergence of
 5506
 5507 Above loop can be parallelized and yet it is in PSPACE. Proof of CJT circuit in RHS to be EXP-complete would immediat
 5508 (*) Let there be exponential number of voters (i.e exponential in number of variables)
 5509 (*) Number of voters = Number of steps in Bounded Halting Problem input Turing Machine = exponential
 5510 (*) Voting halts when all exponential voters have exercised franchise applying their SAT = EXPTIME Turing Mac
 5511
 5512 If there are n boolean functions in total and probability that a boolean function i with goodness $e(i)$ is chosen is:
 5513 $= x(e(i))/n$, where $x(e(i))$ is the number of boolean functions with goodness $e(i)$
 5514 When voter boolean functions have unequal error probabilities, the distribution is Poisson Binomial (which is for ber
 5515
 5516 Thus most generic Majority voting case is when:
 5517 317.3 Voters have unequal decision errors
 5518 317.4 Set of voter boolean functions is an assorted mix of varied error probabilities ranging from 0 to 1.
 5519 317.5 Modelled by Poisson Binomial Distribution
 5520
 5521 In both Majority and Non-majority Choice, error of a boolean function comprises:
 5522 317.6 Voting Error - Misrecorded votes, Probabilistic CNFs
 5523 317.7 Voter Error - Noise Sensitivity of boolean function which has extraneous reasons like correlated flipped
 5524 Randomized decision tree evaluation in 317.7 adds one additional scenario to error matrix of 8 possibilities in 14 ar
 5525
 5526 As mentioned elsewhere in this document and disclaimer earlier, LHS circuit is a lowerbound to RHS circuit for a C-cc
 5527
 5528 From <https://www.math.ucdavis.edu/~greg/zooiology/diagram.xml>, following chain of inclusions are known:
 5529 NC in BPNC in RNC in QNC in BQP in DQP in EXP
 5530 RP in BPP in BQP in DQP in EXP
 5531
 5532 If LHS is a BPNC or RNC or BPP or RP pseudorandom algorithm to unbounded CJT RHS EXP-complete problem under equal goc
 5533 EXP=BPNC (or) EXP=RNC (or) EXP=RP (or) EXP=BPP
 5534 This is rather a serious collapse because the containments include Quantum classes BQP and QNC, implying classical pa
 5535 Let number of voter decision functions with goodness $xi = m(xi)$. Thus $N = m(x1)+m(x2)+m(x3)+...+m(xn)$
 5536 Expected goodness of a PRG choice is:
 5537 $1/N * \sum m(xi) = (x1*m(x1) + x2*m(x2) + x3*m(x3) + ... + xn*m(xn)) / N$
 5538 When all voter functions have goodness 1 then PRG choice in LHS of P(good) has goodness 1.
 5539 For $p=0.5$, RHS goodness is 0.5 and LHS goodness is 0.5 => LHS is in BPNC or RNC or RP or BPP and RHS is BPEXP. If RHS
 5540 EXP=BPNC (or) EXP=RNC (or) EXP=RP (or) EXP=BPP
 5541 when goodness $p=1$ uniformly for all infinite homogeneous electorate.
 5542
 5543 References:
 5544
 5545 317.8 Derandomization Overview - [Kabanets] - http://www.cs.sfu.ca/~kabanets/papers/derand_survey.pdf
 5546 317.9 Unconditional Lowerbounds against advice - [BuhrmanFortnowSanthanam] - <http://homepages.inf.ed.ac.uk/rsanthan/f>
 5547 317.10 EXPTIME-Completeness - [DingZhuDu-KerIKo] - Theory of Computational Complexity - <https://books.google.co.in/b>
 5548 317.11 BPP with advice - <http://people.cs.uchicago.edu/~fortnow/papers/advice.pdf> - "...It can be shown using a trans
 5549
 5550 -----
 5551 318. (THEORY) Yao's XOR Lemma, Hardness of Pr(Good) Majority Voting Function Circuit and Majority Version of XOR Lem
 5552 -----
 5553 Caution: Majority Hardness Lemma derivation is still experimental with possible errors.
 5554
 5555 Hardness of a boolean function is defined as how hard computationally it is to compute the function with a circuit of
 5556 if $Pr(C(x) \neq f(x)) = \delta$ where $C(x)$ computes boolean function $f(x)$, then $f(x)$ δ -hard.
 5557 Majority function is known to have formula of size $O(n^5.3)$ - from Sorting networks of [AjtaiKomlosSzemerédi] and nor
 5558
 5559 Hardness Amplification result by [AndrewYao] states that a strongly-hard boolean function can be constructed from mil
 5560 318.1 Let f be a boolean function with δ -hardness. Therefore there is a circuit $C(x)$ with size s ,such tha
 5561 318.2 Each $f(xi)$ in XOR function $f1$ in 318.1, is either flipped or not flipped. Let Zi be the random variable
 5562 318.3 $Pr(Good)$ majority voting boolean function computes composition of Majority function with Voting functio
 5563 318.4 For simplicity, it is assumed that all voters have same boolean function with hardness δ computable
 5564 318.5 Majority function makes error when the inputs are flipped by some correlation. This Probability that Pr
 5565

318.6 Noise Sensitivity of Majority function is $O(1/\sqrt{n*\epsilon})$ where ϵ is probability of flip per
 318.7 Probability that Majority function is computed incorrectly = NoiseSensitivity +/- randomerror = $[c/\sqrt{n} \epsilon]$
 318.8 Above derivation, if error-free, is the most important conclusion derivable for hardness of $\Pr(\text{Good})$ majc
 318.9 Therefore from 318.7, $\Pr(C(\text{Majn}(f(x1), f(x2), \dots, f(n)) \neq \text{Majn}(f(x1), f(x2), \dots, f(n))) = [c/\sqrt{n*\delta}]$
 318.10 Hardness is amplified if $[c/\sqrt{n*\delta}] \geq \delta$ as follows:

$$\frac{\text{Hardness of Maj+voter composition}}{\text{Hardness of voter function}} = \frac{[c/\sqrt{n*\delta}] + [\text{sum(column2 error entries)}] - [\text{sum(column3 no error entries)}]}{\delta} \gg 1$$

318.11 Let randomerror=r. From above, $[c/\sqrt{n*\delta}] + r \geq \delta$ must be $\gg 1$ for hardness amplification

$$\frac{\text{Hardness of Maj+voter composition}}{\text{Hardness of voter function}} = \frac{[c/\sqrt{n*\delta}] + [\text{sum(column2 error entries)}] - [\text{sum(column3 no error entries)}]}{\delta} \gg 1$$

For large n, $c/\sqrt{n*\delta}$ tends to 0 and If $[\text{sum(column2 error entries)}] - [\text{sum(column3 no error entries)}] \gg \delta$

318.12 318.11 implies that for weakly hard functions (low delta), if quantity in numerator (hardness of majority) is small, then the ratio is large.
 318.13 318.11 also implies that Majority+Voter composition is extremely hard to compute concurring with expor
 318.14 Being extremely hard implies that RHS of $\Pr(\text{Good})$ could be one-way function. One-way functions are hard
 $\Pr(f(f^{-1}(y))=f(x))$ is almost 0.

For example inverse for $\Pr(\text{Good})$ majority voting function is the one that returns set of all voters who voted for a candidate c
 318.15 Conjecture: Circuit for reverse direction (i.e. decomposition of majority to voters who voted in favour of c)
 318.16 Huge hardness of $\Pr(\text{Good})$ RHS also implies that very strong pseudorandom number generators can be constructed
 318.17 The counting problem in 318.15 finds all possible permutations of voters who could have voted in favour of c
 318.18 318.17 implies $\Pr(\text{Majority}(\text{Majority}^{-1}(1)) = \text{Majority}(v1, v2, \dots, vn)) = 1/\#SAT \leq 1/2^n$ in worst case
 318.19 In average case, expected number of SAT assignments to MajoritySAT = $1*1/2^n + 2*1/2^n + \dots + 2^n*1/2^n$
 318.20 318.19 implies Majority is one-way. Therefore FP != FNP and thus P != NP if hardness is amplified in 318.19

References:

318.20 [Impagliazzo-Wigderson] - P=BPP if EXP has $2^{\Omega(n)}$ size circuits - <http://www.math.ias.edu/~avi/PUBLICATIONS/2001/01.pdf>
 318.21 [Trevisan] - XOR Lemma Course Notes - <http://theory.stanford.edu/~trevisan/cs278-02/notes/lecture12.pdf>
 318.22 [Goldreich-Ran Raz] - One-way functions and PRGs - <http://www.wisdom.weizmann.ac.il/~oded/PDF/mono-cry.pdf>
 318.23 Noise Sensitivity of Majority Function - <http://pages.cs.wisc.edu/~dieter/Courses/2008s-CS880/Scribes/lecture11.pdf>
 318.24 Definition of One-way functions - https://en.wikipedia.org/wiki/One-way_function

319. (THEORY) Integer Partitions, Multiway Contests, Hash Table Functions and Ordered Bell Numbers - related to 256 a

Number of hash table functions derived in https://sites.google.com/site/kuja27/IntegerPartitionAndHashFunctions_2014.pdf.
 all possible permutations of hash buckets per partition does not consider order of elements with in each bucket. Bell Number (labeled Bell) is the number of all possible partitions of a set (induced by all possible equivalence relations).
 table is a set of equivalence classes (i.e each bucket is an equivalence class and hash function is the relation), pa
 Ordered Bell Number takes into account order of keys in each bucket and gives all possible Ordered Hash Table Functions.
 estimate of number of hash table functions than plain counting from integer partitions which is unordered. Unordered
 given by: $\sum_{k=0}^n S(n, k)$ where $S(n, k)$ is the Stirling Number of Second kind computing number of ways of partitioning
 into subsets of size exactly k.

Let there be n keys and size of hash table be m. Let $h_i(x) \bmod m$ be a hash function.
 For each h_i
 {
 For each $x < n$
 {
 Compute $h_i(x) \bmod m$ and append to corresponding chain of buckets in hash table
 }
 }
 Above loops create all possible partitions of set of size n. If just the integer partition is reduced to above hash table
 $\sum_{k=1}^m S(n, k) \geq \text{Ordered Bell Number} = \sum_{k=1}^m S(n, k)$

In multipartisan voting with more than 2 candidates, above augmented stirling number is also the number of all possible
 Probability that above multiway majority function has an error (i.e chooses wrong outcome) =
 Probability of changing one voting pattern to the other that changes ranking of candidates

Each voting pattern can be deemed to be a point vertex on an m-dimensional metric space and edges between these vertices
 patterns. If each edge has a probability of occurrence, Probability of flip in voting pattern due to a malpractice is

In a sense the multiway majority hashing previously is a locality sensitive hashing wherein similarity between items
 As mentioned in previous paragraphs, each voting pattern is a point vertex on a metric space and it is necessary to consider
 Probability of multiway majority choosing a wrong outcome = Probability that voting pattern noise flip changes sorted
 319.8 is an NVIDIA CUDA parallel implementation of hash table chaining. 319.9 is a recent parallel locality sensitive

References:

```

5647 -----
5648 319.1 Unordered Bell Number - https://en.wikipedia.org/wiki/Bell\_number
5649 319.2 Ordered Bell Number - https://en.wikipedia.org/wiki/Ordered\_Bell\_number
5650 319.3 Mining Massive Data Sets - [UllmanRajaramanLeskovec] - http://infolab.stanford.edu/~ullman/mmds/book.pdf
5651 319.4 Lowerbounds for Locality Sensitive Hashing - [RyanODonnell] - https://www.cs.cmu.edu/~odonnell/papers/lsh.pdf
5652 319.5 Theory of Partitions - Bell numbers - [GeorgeEAndrews] - http://plouffe.fr/simon/math/Andrews%20G.E.%20The%20T
5653 319.6 Power of Simple Tabulation Hashing - [PatrascuThorup] - http://arxiv.org/pdf/1011.5200v2.pdf - Lemma 4 - Balls
5654 319.7 Balls and Bins, Chained Hashing, Randomized Load balancing - http://pages.cs.wisc.edu/~shuchi/courses/787-F09/
5655 319.8 Parallel Hash tables - Chaining buckets with arrays - http://idav.ucdavis.edu/~dfalcant//downloads/dissertation
5656 319.9 Parallel Locality Sensitive Hashing - [Narayanan Sundaram@@@,Aizana Turmukhametova,Nadathur Satish@@@,Todd Most
5657
5658
5659 -----
5660 320. (BUG-STABILITY ISSUES) Commits - 6 September 2016
5661
5662 VIRGO Linux Kernel Stability Analysis - 2 September 2016 and 6 September 2016
5663
5664 kern.log(s) for Boost::Python invocation of VIRGO system calls with and without crash on two dates have been committed
5665 Logs on 2/9/2016 have a crash as usual in VM paging scatterlist.c.Today's invocation logs show perfect execution of vma
5666
5667 -----
5668 321. (BUG-STABILITY ISSUES) Commits - 8 September 2016
5669
5670 Continued kernel panic analysis of boost::python-VIRGO system calls invocations. Similar pattern of crashes in vma pages
5671 successful panic-free invocation in the end.
5672
5673 -----
5674 322. (BUG-STABILITY ISSUES) Commits - 9 September 2016
5675
5676 Boost::python-VIRGO system calls invocation kernel panic analysis showing some problem with i915 graphics driver interacting
5677 with VIRGO system calls.
5678
5679 -----
5680 323. (THEORY) Complement Functions for Hash Chains, PAC Learning, Chinese Remaindering and Post Correspondence Problem
5681 - important draft additions to http://arxiv.org/pdf/1106.4102v1.pdf
5682
5683 A hash table chain can be viewed as a subset segment of a larger rectangular region. Complement of this subset is another
5684 For example following schematic illustrates hash table complements with respect to chained buckets:
5685
5686 -----
5687 ----- #####
5688 ----- #####
5689 ----- #####
5690 ----- #####
5691
5692 Above diagram has two hash table chains shown in different constituent colors. Together these two cover a rectangular
5693
5694 f(x01) mod m = 0
5695 f(x11) mod m = 1
5696 f(x12) mod m = 1
5697 ...
5698 f(x21) mod m = 2
5699 f(x22) mod m = 2
5700 ...
5701 where xij is the j-th element in i-th chain part in f2 on right. Above tabulation can be solved by Euclid's algorithm
5702 [-m*y + f(x11)] = 1 => f(x11) mod m = 1
5703 Therefore above table can be written as system of congruences:
5704 f(x01) = a01*m + 0
5705 f(x11) = a11*m + 1
5706 f(x12) = a12*m + 1
5707 ...
5708 f(x21) = a21*m + 2
5709 f(x22) = a22*m + 2
5710 ...
5711 Since m is known and all aij can take arbitrary values, complement function for f2 can be constructed by fixing aij as
5712 Boolean 0-1 majority function is a special case of multiway majority function (or) LSH, where hashtable is of size 2
5713 Augmented Stirling Number of Boolean Majority = 2P{n,1} + 2P{n,2}
5714
5715 Chinese Remaindering Theorem states that there is a ring isomorphism for N=n1*n2*n3*....*nk (for all coprime ni) such
5716 X mod N <=> (X mod n1, X mod n2, X mod n3, ...., X mod nk)
5717 (or)
5718 Z/NZ <=> Z/n1Z * Z/n2Z * .... * Z/nkZ
5719 Chinese Remaindering has direct application in hash table chains as they are created in modular arithmetic. K hash functions
5720
5721 From Post Correspondence Problem, if f1 and f2 in schematic diagram are two voting patterns, finding a sequence such
5722 p1p2p3...pm = q1q2q3....qm
5723 is undecidable where pi and qi are parts in voting patterns f1 and f2 as concatenated strings. What this means is that
5724 which makes serialized voters in both patterns equal is undecidable.
5725
5726 Alternative proof of undecidability of Complement Function Construction with PCP :
5727

```

```

5728 Complement Functions are reducible to Post Correspondence Problem. PCP states that finding sequence of numbers i1,i2,
5729      s(i1)s(i2)s(i3)...s(ik) = t(i1)t(i2)t(i3)...t(ik)
5730      where s(ik) and t(ik) are strings is undecidable.
5731
5732 Example inductive base case:
5733 -----
5734 Let f(x) = 2,4,6,8,....
5735 and g(x) = 1,3,5,7,....
5736 f(x) and g(x) are complements of each other.
5737
5738 Define a(i) and b(i) as concatenated ordered pairs of f(xi) and g(xi):
5739      a1 = 2      b1 = 2,3
5740      a2 = 3,4    b2 = 4,5
5741      a3 = 5,6    b3 = 6,7
5742      a4 = 7,8    b4 = 8,9
5743      a5 = 9,10   b5 = 10
5744 [e.g a2 = 3, 4 where g(a2) = 3 and f(a2) = 4; b3= 6,7 where f(b3) = 6 and g(b3) = 7 and so on. Here complement of an
5745
5746 Then, 1,2,3,4,5 is a sequence such that:
5747      a1a2a3a4a5 = b1b2b3b4b5 = 2,3,4,5,6,7,8,9,10
5748 which can be parenthesized in two ways as:
5749      2(3,4)(5,6)(7,8)(9,10) = (2,3)(4,5)(6,7)(8,9)10 = 2,3,4,5,6,7,8,9,10
5750 Each parenthesization is a string representation of a possible way to construct a complement function. Ideally, proce
5751      f(x) = 2,3,5,7,11,...
5752      g(x) = 4,6,8,9,10,12,...
5753
5754      ([2,3],4)(5,6)(7,[8,9,10])(11) = ([2,3])(4,5)(6,7)([8,9,10],11) = 2,3,4,5,6,7,8,9,10,11
5755
5756 Generic inductive case:
5757 -----
5758      (f(x1),succ(f(x1))(f(x2),succ(f(x2)).... = (predec(g(x1),g(x1))(predec(g(x2),g(x2)).... = Z
5759      (or)
5760      concatenation_of(f(xi),g(xi)) = concatenation_of(g(xi),f(xi)) = Z
5761 where succ() and predec() are successor and predecessor functions respectively in lambda calculus jargon and xi take
5762
5763 Two complementation parenthesizations can be drawn as step function where indentation denotes complementary g points
5764
5765      |
5766      | f(1)
5767      |
5768      -----
5769      |           |
5770      |           g(1)
5771      |
5772      -----
5773      |           |
5774      |           f(0)
5775      |
5776      -----
5777      |           |
5778      |           g(0)
5779      |
5780      -----
5781      |           |
5782      |           f(2)
5783      |
5784      -----
5785      |           |
5786      |           g(2)
5787      |
5788
5789 which represent two parenthesization correspondences (sequence on right is staggered by one segment):
5790      (f(1),g(1))(f(0),g(0))(f(2),g(2)) = (f(1))(g(1),f(0))(g(0),f(2))(g(2)) = f(1)g(1)f(0)g(0)f(2)g(2)
5791 Hence x1,x2,x3 take values 1,0,2 for string on left. String on the right despite staggering also takes values 1,0,2 f
5792
5793 Two Generic parenthesizations for f and its complement g are:
5794      [f(x1)][g(y1)f(x2)][g(y2)f(x3)][g(y3)]... = [f(x1)g(y1)][f(x2)g(y2)][f(x3)g(y3)]... = f(x1)g(y1)f(x2)g(y2)f(x3)
5795 where each f(xi) and g(yi) are contiguous streak of set of values of f and g. xi is not necessarily equal to yi. Requ
5796 x1-y1, x2-y2, x3-y3, ... in right and x1, y1-x2, y2-x3, ... in left to make the strings correspond to each other. Her
5797
5798 Another alternative definition of complement function is: function f and its complement g are generating functions fc
5799
5800 Complementation Disjoint Set Cover can be represented as bipartite graph where edges are between two sets A and B. Se
5801
5802 Boolean 0-1 majority special case of Hash chains and Complement Functions:
5803
5804 A hash table of size 2 with 2 chains partitions the set of keys into 2 disjoint sets. Each chain in this hash table i
5805
5806
5807 324. (FEATURE-DONE) PAC Learning for Prime Numbers encoded as binary strings - Commits - 12 September 2016
5808

```

5809 PAC Learning implementation has been augmented to learn patterns in Prime Numbers encoded as binary strings. For each
 5810
 5811
 5812 325. (FEATURE-DONE) PAC Learning for Prime Numbers - Commits - 14 September 2016
 5813
 5814 Some errors corrected in bit positions computation in JSON mappings for PAC learning of Prime Numbers. Logs committed
 5815
 5816
 5817 326. (BUG-STABILITY ISSUES) Boost::Python-VIRGO System calls invocations random kernel panics - Commits - 15 Septembe
 5818
 5819 Further Kernel Panic analysis in i915 driver for Boost::python-VIRGO system calls invocations.
 5820
 5821
 5822 327. (THEORY) Algorithmic Fairness, Pr(Good) Majority Voting Circuit and Algorithmic Decision Making - Related to 14,
 5823
 5824 In Majority Voting hardness analyzed thus far, voting functions of Individual Human Voters are assumed. Recent advanc
 5825 decision making (High Frequency Algorithmic Trading, Predictive Policing etc.,) involve decision making by algorithms
 5826 implicit so far that algorithms cannot have bias. But there is a new emerging field of algorithmic fairness which hig
 5827 bias by machine learning algorithms in decision making (bias could be in training dataset, algorithm's false assumpti
 5828 wrong conclusions based on correlations etc.,) that could subvert stock trading buy-sell decisions, criminal justice
 5829 unfairness could happen in Majority voting also if the voters are algorithms (algorithm internally using a boolean f
 5830 function, past training data to make future decisions among others). Unfair voting algorithms imply that Pr(Good) sum
 5831 converge to 100% and therefore error is non-zero. Unfair voting is detrimental to distributed cloud computing involvi
 5832 choice - e.g loadbalancing of requests get skewed to a node unfairly by bad voting. Most importantly a proof of exis
 5833 voting algorithm implies that LHS of Pr(Good) summation is 1 (From 317.2 least error algorithm is chosen as Non-major
 5834
 5835 References:
 5836
 5837 327.1 Algorithmic Fairness - <https://algorithmicfairness.wordpress.com>
 5838 327.2 Leader Election Algorithms in Cloud - HBase ZooKeeper - [Mahadev Konar - Yahoo] - <http://wiki.apache.org/hadoop>
 5839 327.3 Leader Election and Quorum in ElasticSearch - <https://www.elastic.co/blog/leader-election-in-general> - E
 5840
 5841
 5842 328. (FEATURE-DONE) Locality Sensitive Hashing Implementation - Nearest Neighbours Search - Commits - 16 September 26
 5843
 5844 1.This commit implements locality sensitive hashing in python by wrapping defaultdict with hashing and distance measu
 5845 2.Locality Sensitive Hashing is useful for clustering similar strings or text documents into same bucket and is thus
 5846 classifier and an inverted index too.
 5847 3.In this implementation, very basic LSH is done by having replicated hashtables and hashing a document to each of th
 5848 a random polynomial hash function which itself is aggregation of random monomials.
 5849 4.For a query string, random hash function is again computed and buckets from all hashtables corresponding to this ha
 5850 nearest neighbour set.
 5851 5.Each of these buckets are sieved to find the closest neighbour for that hashtable.
 5852 6.Sorting the nearest neighbours for all hash tables yields a ranking of documents which are in the vicinity of the c
 5853 7.The input strings are read from a text file LocalitySensitiveHashing.txt
 5854 8.Logs with hashtable dumps and nearest neighbour rankings are in testlogs/LocalitySensitiveHashing.out.16September26
 5855
 5856
 5857 329. (FEATURE-DONE) LSH WebCrawler Support - Commits - 19 September 2016
 5858
 5859 Locality Sensitive Hashing now accepts scrapy crawled webpages as datasources.
 5860
 5861
 5862 330. (BUG - STABILITY ISSUES) Boost::Python AsFer-VIRGO system calls kernel panics - Commits - 19 September 2016
 5863
 5864 Boost::python AsFer - VIRGO system call ongoing kernel panic analysis - i915 DRM race condition kernel panic in VM pa
 5865
 5866
 5867 331. (FEATURE-DONE) ZeroMQ based Concurrent Request Servicing CLI - Client and Multithreaded Server Implementation
 5868
 5869 Commits - 21 September 2016
 5870
 5871 1.NeuronRain already has support for RESTful GUI implemented in Python Tornado and NeuronRain code can be executed by
 5872 filling up [HTML](#) form pages.
 5873 2.ZeroMQ has a lowlevel highly performant low latency concurrency framework for servicing heavily concurrent requests
 5874 3.ZeroMQ is a wrapper socket implementation with special support for Request-Reply, Router-Worker, Pub-Sub design pat
 5875 4.Important advantage of ZeroMQ is lack of necessity of lock synchronization (i.e ZeroMQ is lock-free per its documen
 5876 for consistency of concurrent transactions
 5877 5.Hence as a CLI alternative to HTTP/REST GUI interface,a C++ client and server have been implemented based on ZeroMQ
 5878 Router-Dealer-Worker sockets pattern to serve concurrent requests.
 5879 6.ZeroMQ client: ./zeromq_client "<neuronrain executable command>"
 5880 7.ZeroMQ server: invokes system() on the executable arg from zeromq client
 5881 8.With this NeuronRain has following interfaces:
 5882 8.1 telnet client -----> NeuronRain VIRGO ports
 5883 8.2 VIRGO system call clients -----> NeuronRain VIRGO ports
 5884 8.3 AsFer boost::python VIRGO system call invocations -----> NeuronRain VIRGO ports
 5885 8.4 Tornado GUI RESTful -----> NeuronRain VIRGO ports
 5886 8.5 ZeroMQ CLI client/server -----> NeuronRain VIRGO ports
 5887
 5888
 5889

5890 332. (FEATURE-DONE) KingCobra VIRGO Linux workqueue and Kafka Publish-Subscribe Backend Message Queue support in Stre
 5891
 5892 Commits - 22 September 2016
 5893
 5894 1.Streaming_AbstractGenerator has been updated to include KingCobra request-reply queue disk persisted store, as
 5895 a data storage option (reads /var/log/kingcobra/REQUEST_REPLY.queue). Initial design option was to integrate a Kafka
 5896 KingCobra kernelspace servicerequest() function which upon receipt of a message from linux kernel workqueue,also publ
 5897 to a Kafka Topic. But tight coupling of Kafka C Client into KingCobra is infeasible because of conflicts between user
 5898 files of Kafka and kernelspace include header files of Linux. This results in compilation errors. Hence it looks suff
 5899 persisted KingCobra REQUEST_REPLY.queue by a standalone Kafka python client and publish to Kafka subscribers. This le
 5900 by python code on KingCobra queue.
 5901 2.NeuronRain backend now has a support for Kafka Pub-Sub Messaging.
 5902 3.New publisher and subscriber for Kafka (with Python Confluent Kafka) have been written to read data from
 5903 Streaming_AbstractGenerator and to publish/subscribe to/from a Kafka Message Broker-Topic. Thus any datasource that
 5904 AsFer may have(file,HBase,Cassandra,Hive etc.,) is abstracted and published to Kafka. This also unites AsFer backend
 5905 and KingCobra disk persistence into a single Kafka storage.
 5906
 5907
 5908 333. (BUG-STABILITY ISSUES) Boost::Python AsFer-VIRGO system call invocations kernel panic ongoing investigation
 5909
 5910 Commits - 23 September 2016
 5911
 5912 Ongoing Boost::Python AsFer-VIRGO system call invocation kernel panic analysis:
 5913 Random crashes remain, but this time no crash logs are printed in kern.log and finally a successful invocation happen
 5914 same as i915 GEM DRM crash similar to earlier analyses.
 5915
 5916 Pattern observed is as follows:
 5917 1. First few invocations fail with virgo_get() though virgo_malloc() and virgo_set() succeed.
 5918 2. After few failures all virgo calls succeed - virgo_malloc(), virgo_set() and virgo_get() work without any
 5919 3. Sometimes virgo_parse_integer() logs and few other logs are missing. When all logs are printed, success ra
 5920 4. Some failing invocations have NULL parsed addresses. When there are no NULL address parsings, success rate
 5921 5. a rare coincidence was observed: Without internet connectivity crashes are very less frequent. (Intel Micr
 5922 updates playing spoilsport again?).
 5923 6. There have been panic bugs reported on i915 GEM DRM and recent patches for busy VMA handling to it:
 5924 6.1 <https://bugs.launchpad.net/ubuntu/+source/linux/+bug/1492632>
 5925 6.2 <https://lists.freedesktop.org/archives/intel-gfx/2016-August/102160.html>
 5926 7. Intel GPU i915 GEM DRM docs - <https://01.org/linuxgraphics/gfx-docs/drm/gpu/drm-mm.html>
 5927
 5928
 5929 334. (BUG-STABILITY ISSUES) Boost::Python AsFer-VIRGO systemcall/drivers invocations kernel panics - new findings
 5930
 5931 Commits - 28 September 2016
 5932
 5933 Continued analysis of kernel panics after VIRGO systemcalls/drivers code in i915 GPU driver. Has hitherto unseen str
 5934 memory details have been committed to `cpp_boost_python_extensions/testlogs/`.
 5935
 5936
 5937 335. (BUG-STABILITY ISSUES) Boost::Python AsFer-VIRGO systemcall invocations panics - more findings
 5938
 5939 Commits - 29 September 2016
 5940
 5941 Kernel Panic Analysis for Boost::Python AsFer - VIRGO system calls invocations:
 5942 This log contains hitherto unseen crash in python itself deep within kernel (insufficient logs) followed by random -3
 5943 errors. Finally successful invocations happened. Connections between -32,-107 errors and random panics/freezes were a
 5944 ago (Blocking and Non-blocking socket modes). i915 DRM related stacks were not found in kern.log. Random disappearanc
 5945 logs is quite a big travail. Crash within python could be i915 related - cannot be confirmed without logs. Pattern em
 5946 of: Something wrong going on between CPU and GPU while allocating kernel memory in CPU domain - kmalloc() is likely a
 5947 GPU and not CPU - quite a weird bug and unheard of.
 5948
 5949
 5950 336. (BUG-STABILITY ISSUES) VIRGO kernel panics - final findings - 30 September 2016
 5951
 5952 Further kernel panic investigation in VIRGO - probably the last. Logs with analysis have been committed to `cpp_boost_`
 5953 `testlogs/`.
 5954
 5955
 5956 337. (THEORY) Ramsey Theorem, Edge Labelling of Voting Graph and Multiway Majority Function - 5 October 2016 - relate
 5957
 5958 Multiway majority voting can be drawn as a directed graph. There is an edge between vertices v1 and v2 if v1 votes for
 5959 Voting Graph with a weight ≥ 0 . Realworld example of this is web link graph where incoming links to a webpage are v
 5960 outgoing links from a webpage are votes for adjacent pages. PageRank is a special case of Multiway Majority Function
 5961 candidate webpages by a converging random walk markov chain of transition probabilities, with a rider that all webpag
 5962 and candidates making it a peer-to-peer majority voting. PageRank is thus a Non-boolean voting function. If web link
 5963 of depth d, it is equivalent to depth-d recursive majority function. Edge labelling of a graph assigns colors to edg
 5964 (Edge coloring is a special case of labelling with restriction no two adjacent edges are of same color). Voting graph
 5965 labelled where each color of an edge denotes a voter affiliation. Ramsey Number in combinatorics states that there ex
 5966 $v=RN(r,s)$ for every graph of order v, there exists a clique of size r or independent set of size s. For any Voting gr
 5967 implies emergence of a clique or an independent set i.e voters who vote among themselves or who do not vote for each
 5968 graph is complete then Ramsey Theorem implies emergence of monochromatic cliques r (red cliques) or s (blue cliques).
 5969
 5970 References:

5971
 5972 337.1 Ramsey Theorem Lecture Notes - <http://math.mit.edu/~fox/MAT307-lecture05.pdf>
 5973 337.2 Ramsey Theorem - https://en.wikipedia.org/wiki/Ramsey%27s_theorem
 5974
 5975
 5976 338. (THEORY) Van Der Waerden Number, Schur, Szemerédi and Ramsey Theorems, Coloring of Integers and Complement Function
 5977
 5978 Complement Function over Integer sequences can be defined in terms of 2-colorings of the integers. Described previous
 5979 undecidability proof of complementation, a function f and its complement g can be construed as 2-colorings of the Dis
 5980 the set of natural numbers - each color is a function - for example f is red and g is blue.
 5981
 5982 Schur's Theorem for Ramsey coloring of integer sequences states (quoted from <http://math.mit.edu/~fox/MAT307-lecture05.pdf>)
 5983
 5984 " ... Schur's theorem
 5985 Ramsey theory for integers is about finding monochromatic subsets with a certain arithmetic structure. It starts with
 5986
 5987 Theorem 3.
 5988 For any $k \geq 2$, there is $n > 3$ such that for any k -coloring of $1, 2, 3, \dots, n$, there are three integers x, y, z of the
 5989 $x + y = z$... "
 5990
 5991 For complement function special case (i.e 2-coloring of the sequences), Schur Theorem implies that there are always i
 5992
 5993 " ... for any given positive integers r and k , there is some number N such that if the integers $\{1, 2, \dots, N\}$ are c
 5994
 5995 Van Der Waerden Theorem for 2-colorings of natural numbers is equivalent to complementation disjoint set cover of nat
 5996 arity). This implies arbitrarily long monochromatic arithmetic progressions can be found in prime-composite complemen
 5997
 5998 Finding the arithmetic progressions for Van Der Waerden numbers have been formulated as SAT instances which involves
 5999
 6000 Concept of complement graphs have been studied in Perfect Graph Theorem and has strong resemblance to function comple
 6001
 6002 A contrived independent set can be created by adding edges from constituent vertices of the maximum clique which is a
 6003
 6004 Any 2 graphs corresponding to 2 functions defined on same set obtained from previous construction are isomorphic. For
 6005
 6006 In the context of complement function graphs constructed previously, functions are mapped to maximum clique subgraph
 6007
 6008 Szemerédi's Theorem which is the generalization of Van Der Waerden's Theorem states: For any subset A of N of natural
 6009
 6010 Roth Estimate for 2-coloring of integer sequences (in references 338.4 and 338.5) is a measure of order or randomness
 6011 $|\{f(x)\}| = \{N \cdot N^{(1/4 + \epsilon)}\} / 2$
 6012 $|\{g(x)\}| = \{N \cdot N^{(1/4 + \epsilon)}\} / 2$
 6013 with probability equal to natural density of arithmetic progression in $\text{minimax}()$
 6014 Previous approximation with sampling relates size of complement functions, coloring and arithmetic progressions by Rot
 6015
 6016 Complement Graphs F and G constructed previously for function f and its complement g have set of all values of invers
 6017
 6018 Another important question is: Can a complement function polynomial be constructed from constituent monochromatic ari
 6019 Let f_1, f_2, f_3, \dots be functions and g_1, g_2, g_3, \dots be their respective complements. They are represented as graphs constr
 6020 There are 2 possibilities of arithmetic progressions - APs have both colors (elements from both function and its comp
 6021 AP1 = $2x+1 \Rightarrow 1, 3, 5, 7, 9, \dots$
 6022 AP2 = $3x+1 \Rightarrow 1, 4, 7, 11, 14, \dots$
 6023 Merging them gives $1, 3, 4, 5, 7, 9, 10, 11, 13, \dots$ which is a subset of $1, 2, 3, 4, 5, \dots$
 6024
 6025 Scenario1: Monochromatic APs
 6026
 6027 Approximation polynomial for sequence interpolated from constituent monochromatic APs mergesorted = $C(x)$. Let $AP1(x)$,
 6028
 6029 Scenario2: Multichromatic APs
 6030
 6031 When APs have elements of both colors (from both functions $f_k()$ and $g_k()$), parallel mergesort of APs and interpolatic
 6032
 6033 References:
 6034
 6035 338.1 Bound for Van Der Waerden Numbers - <https://www.emis.de/journals/INTEGERS/papers/a20int2005/a20int2005.pdf>
 6036 338.2 Exact Ramsey Theory and Van Der Waerden Numbers by SAT-solvers - [OliverKullmann] - <https://arxiv.org/pdf/1004.3383.pdf>
 6037 338.3 Erdos-Turan Conjecture - https://en.wikipedia.org/wiki/Erd%C5%91s_conjecture_on_arithmetic_progressions - If su
 6038 elements of a set of positive integers diverges, then the set contains arbitrarily long arithmetic progressions
 6039 338.4 Roth Estimate - <http://matwbn.icm.edu.pl/ksiazki/aa/aa9/aa9125.pdf> - Consider a two coloring of set of natural
 6040 338.5 Roth Estimate is nearly sharp - Beck, J. Combinatorica (1981) 1: 319. doi:10.1007/BF02579452 - <http://link.springer.com/article/10.1007/BF02579452>
 6041 338.6 Discrepancy in Arithmetic Progressions - [MatousekSpencer] - Roth estimate is best possible - $ROTH(N) \leq N^{1/4}$
 6042 338.7 Discrepancy Minimization by Walking on Edges - [BansalLovettMeka] - <https://arxiv.org/pdf/1203.5747v2.pdf> - Thi
 6043 338.8 Fourier Interpolation of n data points with polynomial of degree m - <http://www.muskingum.edu/~rdaquila/m350/fc.html>
 6044 338.9 Fourier Analysis and Szemerédi's Theorem - Roth's Argument - Documenta Mathematica ICM Extra Volume 1998 - <http://www.muskingum.edu/~rdaquila/m350/fc.html>
 6045 338.10 Hales-Jewett Theorem - [MichelleLee] - <http://www.math.uchicago.edu/~may/VIGRE/VIGRE2009/REUPapers/Lee.pdf> - g
 6046 338.11 Polynomial Interpolation from Low Discrepancy Arithmetic Progressions - [The Discrepancy Method: Randomness and
 6047 338.12 Sequences Generated By Polynomials - [CorneliusSchultz] - https://www.researchgate.net/profile/E_Cornelius_Jr
 6048 338.13 Polynomial Points, Green-Tao Theorem and Arithmetic Progressions - [CorneliusSchultz] - <https://cs.uwaterloo.ca/~schultz/>
 6049 338.14 Recent Advanced Theorems in k -coloring of integer sequences - <http://people.math.sc.edu/lu/talks/ap4.pdf> - the
 6050
 6051

6052 339. (FEATURE-DONE) Boyer-Moore Streaming Majority Algorithm - Commits - 7 October 2016
 6053
 6054 This commit implements Boyer-Moore algorithm for finding Majority element in Streaming Sequences. It uses the Streami
 6055 Abstraction for input streaming datasource. Logs have been committed to python-src/testlogs/
 6056
 6057
 6058 340. (FEATURE-DONE) GSpan Graph Substructure Mining Algorithm Implementation - Commits - 13 October 2016 and 14 Octok
 6059
 6060 1.Graph Substructure Mining GSpan algorithm implementation with logs in testlogs/
 6061 2.This code requires the Graph vertices to be labelled by unique integers
 6062 3.Integer labelling of vertices makes it easier for DFSCode hashes to be generated uniquely.
 6063
 6064
 6065 341. (THEORY) Graph Mining Algorithms and Recursive Gloss Overlap Graph for text documents - Document Similarity
 6066
 6067 Recursive Gloss Overlap Algorithm implementations in python-src/InterviewAlgorithm and its Spark Cloud Variants gener
 6068 with word labels from Text Documents. GSpan algorithm implemented in (340) mines subgraphs and edges common across gr
 6069 This allows extraction of common patterns amongst text document graphs and thus is an unsupervised similarity cluster
 6070 text analytics. GSpan has provisions for assigning minimum support for filtering patterns which amounts to finding pr
 6071 keywords in recursive gloss overlap graphs.
 6072
 6073
 6074 342. (FEATURE-DONE) Graph Mining Recursive Gloss Overlap Graph for text documents - Document Similarity
 6075
 6076 Commits - 17 October 2016
 6077
 6078 1.Code changes have been done to choose between numeric and word labelling of Graph vertices in GSpan GraphMining imp
 6079 2.New file GraphMining_RecursiveGlossOverlap.py has been added to JSON dump the Recursive Gloss Overlap graph of a te
 6080 3.New directory InterviewAlgorithm/graphmining has been created which contains the numeric and word labelled Recusive
 6081 graphs of 5 example text documents in topic class "Chennai Metropolitan Area Expansion"
 6082 4.logs for common edges mined between two Recursive Gloss Overlap document graphs has been committed in testlogs/
 6083 5.Spidered web text has been updated
 6084 6.GraphMining_RecursiveGlossOverlap.py JSON dumps the RG0 edges into a text file and GraphMining_GSpan.py JSON loads
 6085 InterviewAlgorithm/graphmining/
 6086
 6087
 6088 343. (THEORY) Streaming Majority and 2-Coloring(Complement Functions) - related to 14.16 and 19,24,323,338,339 - impc
 6089 updates to <http://arxiv.org/pdf/1106.4102.pdf> - 1 November 2016
 6090
 6091 In simple 2 candidate majority voting done on stream of votes, a 2-colored sequence of votes by voters is generated.
 6092 already mentioned in infinite majority (Erdos Discrepancy Theorem) - 14.16.Each color symbolizes a candidate voted. T
 6093 he sequence of votes into 2 monochromatic sets. Obviously, if the voters are uniquely identified by a sequence numbe
 6094 theorems imply there are monochromatic and multichromatic arithmetic progressions in voter unique identities. Boyer-M
 6095 computes streaming majority (implemented in 339).
 6096
 6097
 6098 344. (BUG-STABILITY ISSUES) AsFer-VIRGO Boost::Python system calls invocations analysis - commits - 4 November 2016
 6099
 6100 Some resumed analysis of AsFer-VIRGO boost::python invocations of VIRGO memory system calls which were stopped few mc
 6101 The i915 DRM GEM error is highly reproducible pointing something unruly about it. No logical reason can be attributed
 6102 some kernel sync issues. This further confirms that there is nothing wrong with VIRGO layer of Linux kernel and Linu
 6103 within inherently has a chronic problem.
 6104
 6105
 6106 345. (THEORY) Polynomial Reconstruction (PR) Problem, Error Correcting Codes and 2-Coloring/Complement Functions - im
 6107 draft updates to <http://arxiv.org/pdf/1106.4102.pdf> - 10 November 2016 and 17 November 2016
 6108
 6109 Polynomial Reconstruction Problem states that:
 6110 Given a set of n points $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ recover all polynomials p of degree less than k such that $p(x_i) = y_i$
 6111 for maximum of i points in $\{1, 2, 3, \dots, n\}$. In other words PRP is a curve-fitting interpolation problem and is related
 6112 to Error Correcting problems like List Decoding (list of polynomials approximating a message one of which is correct), Re
 6113 2-Coloring scheme algorithms and Complement Function constructions are alternative spectacles to view the Polynomial
 6114 Problem i.e Complement Function and 2-Coloring are special settings of Polynomial Reconstruction with exact curve fit
 6115
 6116 References:
 6117
 6118 345.1 Polynomial Reconstruction and Cryptanalysis - Berlekamp-Welch, Guruswami-Sudan algorithms - <https://eprint.iacr.org/2011/570.pdf>
 6119 345.2 Hardness of Constructing Multivariate Polynomials over Finite Fields - [ParikshitGopalan,SubhashKhot,RishiSaket
 6120 345.3 Lagrange Interpolation and Berlekamp-Welch PRP algorithm - [SadhkanRuma] - https://www.academia.edu/2756695/Evaluation_of_Berlekamp-Welch_Algorithm.pdf
 6121
 6122
 6123
 6124 346. (FEATURE-DONE) Major rewrite to Rule Search for Sequence Mined Astronomical Datasets
 6125
 6126 Commits - 17 November 2016
 6127
 6128 1. Rule Search script has been updated to include Cusps too to find cross-cusp patterns
 6129 2. SequenceMining.py script has been updated specific to NeuronRain AsFer Research version
 6130 3. Rule Search script has been rewritten on top of SourceForge revision 945 which was overwritten in later
 6131 commits by replicated GitHub version (NeuronRain Enterprise)
 6132 4. Logs for above have been committed to testlogs (next commit)

6133 5. MinedClassAssociationRules.txt has been updated to latest sequence mining version with Cusps.
 6134 6. This commit is specific to NeuronRain Research version in SourceForge and is not replicated in GitHub NeuronRain
 6135 Enterprise repository.
 6136
 6137
 6138 347. (THEORY) Data written in electronic storage devices (e.g CD/DVD) and 2-Coloring/Complement Functions - important
 6139 draft updates to <http://arxiv.org/pdf/1106.4102.pdf> - 24 November 2016 and 28 November 2016
 6140
 6141 CD/DVD storage devices contain binary data burnt on concentric cylindrical tracks. A radial line from central bull's
 6142 complete circle in a scan covers 2^n possible binary strings. In the best case all 2^n words are distinct. Total Numb
 6143 2^n words are in fibonacci sequence:
 6144 $f(n) = 2f(n-1) + 2^{n-1}$
 6145 with $f(0)=0$ and $f(1)=1$. In 2-coloring parlance, DVD is 2-colored with 1(red) and 0(blue) where number of monochromati
 6146 bounded by:
 6147 $f(n) = 2f(n-1) + 2^{n-1}$ out of minimum $n*2^n$ possible bits on the storage. Thus any data written to storage
 6148 $f(3) = 2f(2) + 2^2 = 2(2f(1) + 2) + 2^2 = 8 + 4 = 12$ minimum possible monochromatic bit positions
 6149 This has some applications of Hales-Jewitt Theorem for multidimensional 2-coloring - storage device always has a monc
 6150 00
 6151 01
 6152 10
 6153 11
 6154 are minimum possible distinct binary words swept by a radial scan of the circle and there are $f(2)=2f(1) + 2 = 4$ monc
 6155
 6156 The previous question has been answered in 2.10. There could be \/ shaped gaps in circular arrangement of 2^n binary
 6157 $g(n) = f(n) + f(n-1) + f(n-2) + \dots + f(1) + f(0)$
 6158 Thus $g(n)$ is the tightest bound for number of 1s and 0s. Prefix "minimum" has been added in this bound because repeti
 6159
 6160 348. (FEATURE-DONE) NeuronRain C++-Python System calls invocation - Commits - 29 November 2016
 6161
 6162 1. Further analysis of NeuronRain AsFer-VIRGO boost::python system calls invocation - there has been
 6163 an erratic -32 and -107 errors
 6164 2. But VIRGO system calls work without problems - malloc, set and get work as expected
 6165 3. There is a later panic outside VIRGO code but logs have not been found.
 6166 4. Logs for this have been added in testlogs/
 6167 5. boost C++ code has been rebuilt.
 6168
 6169
 6170 349. (THEORY) Kleinberg Lattice , Random Graph Ontologies, Bose-Einstein model and Recursive Gloss Overlap algorithm
 6171
 6172 Result of $r=2$ in [Kleinberg - 202.19] is an equilibrium state. Random shortcut edges are created with some probabilit
 6173 random edge probability($d(n1,n2)$) = $|l(n1,n2)|^{(-r)}$ where l is the lattice distance
 6174 When r is less than 2 or close to zero, random edges are as numerous as lattice edges (random edges exist in abundanc
 6175
 6176 Above small world phenomenon can be mapped to ontology of linguistic concepts/words. Let set of all concepts/words fc
 6177 Kleinberg criterion of $r=2$ is an alternative way to assess the meaningfulness of a document. Document definition grap
 6178 $r * \log(l(n1,n2)) = \log(1/d(n1,n2))$
 6179 When $r=2$:
 6180 $2\log(l(n1,n2)) = \log(1/d(n1,n2))$
 6181 which stipulates conditions for high intrinsic merit for a document in terms of lattice distance and random edge prot
 6182
 6183 Kleinberg Lattice , Random Graph Ontologies, Bose-Einstein model and Recursive Gloss Overlap algorithm
 6184
 6185 Bose-Einstein model for networks relates fitness of a vertex (ability to attract edges) in a graph and Bose-Einstein
 6186
 6187 References:
 6188
 6189 349.1 Bose-Einstein Model and Complex Networks - [https://en.wikipedia.org/wiki/Bose-Einstein_condensation_\(ne](https://en.wikipedia.org/wiki/Bose-Einstein_condensation_(ne)
 6190 349.2 Golden mean as a clock cycle of brain waves - <http://www.v-weiss.de/chaos.html> - "...In 2001 Bianconi and Barat
 6191
 6192 350. (THEORY) Randomness, Quantum Machine Learning and a Schroedinger Cat simulation of learning patterns in BigData
 6193
 6194 Caution: This section postulates a drastically new theory mapping quantum mechanics to learning patterns in bigdata w
 6195
 6196 State of a subatomic particle is defined by a wave function on Hilbert Space (Complex State Vector Space). In Dirac r
 6197
 6198 In terms of BigData analytics, learning a variable in a blackbox is reducible to Schroedinger's Cat paradox. Assuming
 6199 Any BigData set with apparent randomness can be construed as a series of outputs over time generated by a randomized
 6200
 6201 An alternative formulation of F+G is:
 6202 F is the quantum randomness source (e.g Double slit) and G invokes (or measures) F to produce a datastream over time.
 6203
 6204 There are two levels of learning possible:
 6205 *) Learning within blackbox - Learning patterns from observations of F+G. F+G are pre-equipped with ability to learn
 6206
 6207 *) Learning outside blackbox - This is obvious contradiction mentioned previously because dataset generated by F+G is
 6208
 6209 Thus above seems to imply learning is impossible with quantum randomness.
 6210
 6211 References:
 6212
 6213

6214 -----
6215 350.1 Feynman Lectures on Physics - [RichardFeynman] - Volume 3 - Chapter 1 and 2
6216 350.2 Emperor's New Mind - [RogerPenrose] - Chapter 6 - Quantum Magic and Quantum Mystery
6217 350.3 Quantum Randomness and Logical Independence - <https://arxiv.org/pdf/0811.4542v2.pdf> - *Mutually independent logi*
6218 -----
6219 351. (THEORY) Quantum Parallelism, Quantum Interference, Integer Factoring, Periodicity Finding, Polynomial Reconstru
6220 Complement Function/2-Coloring - related to 24,34,323,338,345 and 347 - 29 December 2016 - important draft updates to
6221 - <http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactoriz>
6222 - <http://arxiv.org/pdf/1106.4102.pdf>
6223 -----
6224 Discrete Hyperbolic Factorization draft in 34 claims (disputed because of input size though references exist to prove
6225 *) Quantum Parallelism in which a function $f(x)$ is computed to get many values of $f(x)$ in parallel
6226 *) Quantum Interference by Hadamard transform where cancellation occurs ($|0\rangle = 1/\sqrt{2}(|0\rangle + |1\rangle)$ and $|1\rangle =$
6227 -----
6228 Period Finding in Quantum Computation finds smallest r such that $f(x)=f(x+r)$ and Shor's factorization internally appl
6229 -----
6230 References:
6231 -----
6232 351.1 Quantum Computation Course notes - Order Finding, Fermat's Little Theorem and Simon, Shor Factorization algorit
6233 351.2 Progress on Quantum Algorithms - [PeterShor] - <http://www-math.mit.edu/~shor/papers/Progress.pdf>
6234 -----
6235 352. (FEATURE-DONE) Recommender Systems Implementation based on ThoughtNet Hypergraph - 1 January 2017
6236 -----
6237 *) Input to python-src/DeepLearning_ReinforcementLearningRecommenderSystems.py is a set of observations which are use
6238 (shopping cart items, academic articles read by user etc.,) and already built thoughtnet hypergraph history is search
6239 evocatives from the input
6240 *) Evocatives returned from ThoughtNet hypergraph are items recommended relevant to user's activities.
6241 *) This technique of recommendation is more qualitative than usual methods of Collaborative Filtering and mimicks the
6242 thought process of "relevance based evocation" based on past experience (i.e ThoughtNet history)
6243 *) New input text file and folder RecommenderSystems has been added to python-src with Neo4j Graph Database support
6244 *) Logs have been committed in testlogs/
6245 -----
6246 353. (FEATURE-DONE) Kafka data storage for Streaming Abstract Generator - 2 January 2017
6247 -----
6248 Kafka Streaming Platform has been added as a data storage in Streaming Generator Abstraction Single-Window entrypoint
6249 code for a neuronraindata topic polls for incoming messages in iterator. As an example Streaming CountMeanMinSketch i
6250 been updated to source streamed data published in Kafka.
6251 -----
6252 354. (FEATURE-DONE) An example usecase of Recommender Systems for online shopping cart - 2 January 2017
6253 -----
6254 *) RecommenderSystems folder has been updated with new text file from an example past shopping cart history items (e.
6255 topics in Amazon online bookstore)
6256 *) From the above edges a Hypergraph is created by classifying the shopping cart items into classes and constructing
6257 classes (by Recursive Gloss Overlap Graph maximum core number classifier)
6258 *) Text files for above usecase have .shoppingcart suffixes
6259 *) Above shopping cart hypergraph has a past history of items chosen by a user from variety of topics.
6260 *) New input file RecommenderSystems.shoppingcart.input.txt has present items in user's shopping cart and new items h
6261 user based on present choice and past history.
6262 *) For this, items in present shopping cart are lookedup in past sales history Hypergraph created previously and recc
6263 *) Items in present shopping cart are looked up in two ways: 1) By classifying with Recursive Gloss Overlap graph and
6264 less than a threshold (presently core number 5) and 2) Raw token lookup
6265 *) Logs for these two lookups based Recommendations generated are committed to testlogs/
6266 -----
6267 An important note: Rationale for Hypergraph based past history is that a meaningful text can be classified on multipl
6268 supervised classifiers which classify text on exactly one class. This is more realistic because text can delve into m
6269 -----
6270 355. (FEATURE-DONE) More detailed shopping cart example 2 for RG0+ThoughtNet based Recommender System - 3 January 201
6271 -----
6272 *) python-src/DeepLearning_ReinforcementLearningRecommenderSystems.py has been updated to choose top percentile class
6273 so that vertices with large core numbers get more weightage.
6274 *) New shoppingcart2 product reviews text has been added and corresponding Hypergraph history has been created. This
6275 product description with an assorted mix (TV reviews, Washing Machine reviews, Home Theatre reviews etc.,) - python-s
6276 python-src/RecommenderSystems/RecommenderSystems_Hypergraph_Generated.shoppingcart2.txt
6277 *) New input file python-src/RecommenderSystems.shoppingcart2.input.txt has been added with an example product (TV).
6278 *) Recommender System chooses relevant TV products from Hypergraph history and displays to user.
6279 *) Logs have been committed to testlogs/
6280 -----
6281 356. (THEORY) NEXP not in non-uniform ACC, $P(\text{Good})$ majority voting circuit and some contradictions - 4 January 2017 a
6282 - related to all $P(\text{Good})$ majority voting circuit related points in this document (e.g 14,53 etc.,)
6283 -----
6284 RHS of $P(\text{Good})$ majority voting circuit has exponential size with unrestricted depth in worst case and is in EXP (if d
6285 result by [RyanWilliams] limits that NEXP is not in ACC (AC circuits with counter mod[m] gates which output 1 if sum
6286 of m). Non uniform ACC is contained in TC and AC is contained in ACC (AC in ACC in TC). This makes a contradiction if
6287 percolation circuit in non-uniform NC (NC/poly). If $P(\text{Good})$ binomial coefficient series summation converges to 100%,
6288 more counterexample implying some or all of the following:
6289 -----
6290

```

6295      *) There is no 100% efficient RHS majority voting boolean function composition
6296      *) There is no 100% efficient LHS boolean function (pseudorandomly chosen boolean function, ranked by social c
6297      *) RHS Majority voting is not in NEXP.
6298      *) LHS pseudorandom choice boolean cannot have a non-uniform NC circuit
6299 Above, "efficiency" implies "No error" cases in scenarios matrix of 53.14 and a ninth error scenario of Randomized De
6300 -----
6301      x           |   f(x) = f(x/e)   |   f(x) != f(x/e) Noise   |
6302 -----
6303      x in L, x/e in L   |   No error   |   Error   |
6304 -----
6305      x in L, x/e not in L   |   Error   |   No error if f(x)=1,f(x/e)=0   |
6306      |                   |                   |   else Error   |
6307 -----
6308      x not in L, x/e in L   |   Error   |   No error if f(x)=0,f(x/e)=1   |
6309      |                   |                   |   else Error   |
6310 -----
6311      x not in L, x/e not in L   |   No error   |   Error   |
6312 -----
6313 -----
6314      x           |   f(x)   |
6315 -----
6316      Randomized Decision tree evaluation   |   No error   |   Error   |
6317
6318 If LHS social choice ranking function is Interview algorithm which is a PSPACE=IP algorithm (by straightforward reduc
6319
6320 There are natural processes like Soap Bubble formation known to solve Steiner Tree NP-hard problem efficiently. Soap
6321 glass plates are formed and bubbles are connected by line segments of optimum total length which converge at Steiner
6322 also a natural process with human element involved. Does human judgement overwhelm algorithmic judgement in decision
6323 open question. If neural networks are algorithmic equivalents of human reasoning, then each voter decision function c
6324 non-uniform TC neural network. Error of majority voting is then equal to error of this majority function + neural net
6325
6326 Previous matrix of 10 scenarios basically subdivides the traditional BP* definition which says: For x in L, a BP* tur
6327      *) (f(x)=f(x/e)) in which case two correlated strings one in L and other not in L are both accepted (false po
6328      *) (f(x) != f(x/e) - Noise sensitivity) in which case two correlated strings in L or not in L are erroneously
6329      *) Previous two are input related while the last scenario with error in decision tree evaluation is internal
6330
6331 This false positive + false negative voter judgement error applies to BPTC NC+neural network circuit composition als
6332
6333 References:
6334 -----
6335 356.1 NEXP not in non-uniform ACC - [RyanWilliams] - http://www.cs.cmu.edu/~ryanw/acc-lbs.pdf
6336 356.2 Soap Bubble Steiner Tree and P=NP - [ScottAaronson] - https://arxiv.org/pdf/quant-ph/0502072v2.pdf
6337 356.3 Constant depth Threshold circuits - http://people.cs.uchicago.edu/~razborov/files/helsinki.pdf
6338 356.4 Circuit Complexity of Neural networks - https://papers.nips.cc/paper/354-on-the-circuit-complexity-of-neural-ne
6339 356.5 Exact Threshold circuits - http://www.cs.au.dk/~arnsfelt/Papers/exactcircuits.pdf
6340 356.6 Universal Approximation Theorem - [Cybenko] - https://en.wikipedia.org/wiki/Universal\_approximation\_theorem - A
6341 356.7 L* algorithm for exact learning of DFAs - [Dana Angluin] - https://people.eecs.berkeley.edu/~dawnsong/teaching/
6342 356.8 Efficient Learning Algorithms Yield Circuit Lower Bounds - [Lance Fortnow] - http://lance.fortnow.com/papers/f
6343
6344
6345 -----
6346 357. (FEATURE-DONE) PythonSpark+Cython Interview Algorithm cloud implementation update - 4 January 2017 - related to
6347
6348 PythonSpark+Cython Cloud Implementation of Interview Algorithm has been updated to print average clustering coefficie
6349 graph for text. Average clustering coefficient is average(per node clustering coefficient) for all nodes where cluste
6350 a vertex is a ratio of edges to neighbours to all possible edges to neighbours (or) amount of "cliqueness" of each ne
6351 vertices in a graph. This adds an alternative way for computing intrinsic merit of a document recursive gloss overlap
6352 349 (Kleinberg's small world graph and clustering coefficient = 2). Average clustering coefficient supplements the intr
6353 score in deciding semantic relatedness of a graph. Closer the clustering coefficient is to 2, it is easier to find pa
6354 and greater the linguistic meaningfulness.
6355
6356 -----
6357 358. (THEORY) P(Good) non-majority versus majority social choices, BPTC and PSPACE classes - related to 317,356 - 6 J
6358
6359 Caution: Following tries to prove a major lowerbound result with some assumptions and is subject to errors.
6360
6361 Main motivation for so much emphasis on P(Good) binomial summation convergence is: LHS is non-majority social choice
6362 social choice and convergence to 100% on both sides implies LHS and RHS are of equal merit with varying complexity cl
6363 choice process is as follows:
6364
6365 foreach(voter)
6366 {
6367     Interview the voter (a PSPACE-complete problem where polynomial number of question-answering reduces to prover
6368 }
6369 Rank the voters by merit and choose the topmost as non-majority social choice - voting is obviated.
6370
6371 It is interesting to note that web search engines use both non-majority (Ranking by merit) and majority choice (e.g F
6372
6373 -----
6374 359. (THEORY) KRW Conjecture on Boolean Function Composition, Non-majority (PSPACE) and Majority (harder than PSPACE)
6375 related to 14,53,311,356 - 7 January 2017
6376

```

6376 Previous point mooted the idea of the parallel interview of voters and ranking them as a non-majority social choice.
 6377 the interview algorithm scores of individual voters and finding topmost. Sorting of numbers is in AC=NC=TC (Sorting r
 6378 [ChandraStockMeyerVishkin] Constant Depth Reducibility for Sorting - <http://www.cstheory.com/stockmeyer@sbcglobal.net>
 6379 Threshold circuits for sorting) and each voter's PSPACE-complete interview circuit is input to NC sorting circuit to
 6380
 6381 This creates a following intriguing possibility: If RHS majority voting has voter functions harder than PSPACE (i.e E
 6382
 6383 References:
 6384 -----
 6385 359.1 Karchmer-Raz-Wigderson (KRW) Conjecture of Boolean Function Composition and Information Complexity - <http://cs>.
 6386 -----
 6387 360. (THEORY) Non-majority social choices - Interview Ranking Function and Pseudorandom Choice Function - 11 January
 6388 317, 359 and all other non-majority versus majority voting points
 6389 -----
 6390 Previous sections mentioned about two possible ways of non-majority social choice:
 6391 *) Parallel interview of voters and ranking based on sorted interview scores
 6392 *) Psuedorandom choice
 6393
 6394 -----
 6395 Interview circuit:
 6396 -----
 6397 Error in interview circuit which is an NC sorting network with PSPACE-complete voter interviews as inputs is defined
 6398 False positives + False negatives + False questions = Percentage of wrong answers marked as right + Percentage of rig
 6400
 6401 For sorting purposes output of TQBF is not a binary 0 or 1 but a binary string with value equal to number of correct
 6402 other boolean functions sensitivity of TQBF $\phi(q_1, a_1, q_2, a_2, q_3, a_3, \dots, q_n, a_n)$ is defined as how flipping of a_i and q_i
 6403 Formally,
 6404 Sensitivity(TQBF) = $\Pr(TQBF(X) \neq TQBF(X_{\text{correlated}}))$ where $X_{\text{correlated}}$ is an interview with erroneous question
 6405
 6406 Thus sensitivity captures the error in interview. It has to be noted that wrong questions also measure the flaw in in
 6407
 6408 -----
 6409 Pseudorandom Choice:
 6410 -----
 6411 Set of all voter decision functions is partitioned into n sets where each set has goodness x_i . Here goodness of a vot
 6412 is defined as: 1-error(f).
 6413
 6414 Let number of voter decision functions with goodness $x_i = m(x_i)$. Thus $N = m(x_1) + m(x_2) + m(x_3) + \dots + m(x_n)$
 6415 Expected goodness of a PRG choice is:
 6416 $1/N * \sum m(x_i) = (x_1 * m(x_1) + x_2 * m(x_2) + x_3 * m(x_3) + \dots + x_n * m(x_n)) / N$
 6417 When all voter functions have goodness 1 then PRG choice in LHS of $P(\text{good})$ has goodness 1.
 6418
 6419 These two non-majority choices are just hypothetical examples of how a social choice can be made without voting. In r
 6420 social choice occurs is quite complex and determined by various factors of society (economic disparities, ethnicity
 6421
 6422 -----
 6423 361. (FEATURE-DONE) Commits - 11 January 2017 - DeepLearning Convolution Networks update
 6424
 6425 Some changes done to Convolution computation:
 6426 *) Made sigmoid perceptron optional in final neural network from Maxpooling layer so that weighted sum is printed ins
 6427 *) This causes the convolution network to be very sensitive to presence of pattern
 6428 *) 2 more example bitmaps have been added with varying degree of pattern prominence (a pronounced X and a thin 1)
 6429 *) With this final neurons from maxpooling layer print values of neurons which quite closely reflect the pattern's ma
 6430 *) This can rank the bitmaps in increasing degree of magnitude of pattern presence
 6431 *) Logs for this have been committed to testlogs
 6432
 6433
 6434 -----
 6435 362. (FEATURE-DONE) DeepLearning Convolution Network - an example pattern recognition from bitmap images - 12 January
 6436
 6437 *) Few more bitmap images have been included with same pattern but of different sizes
 6438 *) There are 5 patterns and 9 bitmaps:
 6439 - Thin X and Boldfaced X
 6440 - Thin 0 and Boldfaced 0
 6441 - Thin 8 and Boldfaced 8
 6442 - No pattern
 6443 - Thin 1 and Boldfaced 1
 6444 *) Expectation is that Convolution Network final neuron layer must output similar values for same pattern and differe
 6445 for different patterns
 6446 *) pooling_neuron_weight has been reintroduced in final neuron layer of 10 neurons each with a randomly chosen weight
 6447 *) Logs show for all 10 neurons, final neural activation values are close enough for similar patterns and different f
 6448 *) Thus Convolution Network which is a recent advance in DeepLearning works quite well to recognize similar image pat
 6449
 6450 In above example , 9th and 10th neurons output following values. Example 11 and 12 are similar patterns - 0 and 0. Ex
 6451 #####
 6452 Inference from Max Pooling Layer - Neuron 8
 6453 #####
 6454 Example 11:
 6455 #####
 6456 [27.402311485751664]

```

6457 #####
6458 Example 12:
6459 #####
6460 [27.36740767846171]
6461 #####
6462 Example 21:
6463 #####
6464 [32.15200939997122]
6465 #####
6466 Example 22:
6467 #####
6468 [30.835940458495205]
6469 #####
6470 Example 3:
6471 #####
6472 [17.133246549473675]
6473 #####
6474 Example 41:
6475 #####
6476 [29.367605168715038]
6477 #####
6478 Example 42:
6479 #####
6480 [27.446193773968886]
6481 #####
6482 Example 51:
6483 #####
6484 [22.12145242997834]
6485 #####
6486 Example 52:
6487 #####
6488 [24.17603022706531]
6489 #####
6490 Inference from Max Pooling Layer - Neuron 9
6491 #####
6492 Example 11:
6493 #####
6494 [24.667080337176497]
6495 #####
6496 Example 12:
6497 #####
6498 [24.635666910615544]
6499 #####
6500 Example 21:
6501 #####
6502 [28.941808459974094]
6503 #####
6504 Example 22:
6505 #####
6506 [27.757346412645685]
6507 #####
6508 Example 3:
6509 #####
6510 [15.424921894526316]
6511 #####
6512 Example 41:
6513 #####
6514 [26.435844651843524]
6515 #####
6516 Example 42:
6517 #####
6518 [24.70657439657199]
6519 #####
6520 Example 51:
6521 #####
6522 [19.914307186980512]
6523 #####
6524 Example 52:
6525 #####
6526 [21.763427204358788]
6527 #####
6528 -----
6529 363. (FEATURE-DONE) DeepLearning BackPropagation Implementation Update - 17 January 2017
6530 -----
6531 *) DeepLearning BackPropagation code has been changed to have 3 inputs, 3 hidden and 3 output layers
6532 with 3*3=9 input-hidden weights and 3*3=9 hidden-output weights with total of 18 weights
6533 *) Software Analytics example has been updated with a third input and logs for it have been committed
6534 to testlogs/.
6535 *) Logs include a diff notes of how to extend this for arbitrary inputs and accuracy of backpropagation
6536 which beautifully converges at ~10^-26 error after ~1000000 iterations.
6537

```



```

6619 Assuming for all ai=bi=a:
6620     Stability(Interview) = a^2 * (Expectation(w1*z1) + Expectation(w1*z2) + .... + Expectation(wn*zn))
6621
6622 Expectation(wi*zk) = 0*0*1/4 + 0*1*1/4 + 1*0*1/4 + 1*1*1/4 for 4 possible values of (wi,zk) each with probability 1/4
6623
6624 => Stability(Interview) = a^2 * (n^2 * 0.25) = a^2*n^2/4
6625
6626 Stability(Interview) = a^2*n^2/4 < 1 => a < 2/n
6627
6628 If Stability(Interview) > Stability(Majority), BKS conjecture is true.
6629
6630 => a^2*n^2 / 4 > 1 - 2/pi
6631 => a > 2/n * sqrt(1-2/pi)
6632 => a > 1.2056205488/n [For minimum case of n=2, a > 0.6028102744]
6633
6634
6635 Thus for Stability(Interview) to exceed Stability(Majority) and BKS Conjecture to be true , weight per answer has to
6636
6637 Stability is alternatively defined as:
6638     (+1)*Pr(f(x) = f(y)) + (-1)*Pr(f(x) != f(y))
6639 which is just expansion of Expectation and there are two random variables (+1 for f(x)=f(y)) and (-1 for f(x) != f(y)
6640 => Stability(f(x)) = 1-2*Pr(f(x) != f(y))
6641 => Stability(f(x)) = 1-2*Sensitivity(f(x))
6642 => Sensitivity(f(x)) = 0.5-0.5*Stability(f(x))
6643
6644 NoiseSensitivity(Interview) which is the dual of Stability is defined as:
6645     NoiseSensitivity(Interview) = 0.5-0.5*Stability(Interview) = 0.5-0.5*a^2*n^2/4
6646
6647
6648 367. (FEATURE-DONE) Commits - 25 January 2017 - related to 2.9 and 345
6649
6650 Berlekamp-Welch Polynomial Reconstruction Decoder Implementation (for Reed-Solomon codes, texts, numerical points etc
6651
6652 *) Implements Berlekamp-Welch Polynomial Reconstruction Algorithm for reconstructing data from errors.
6653 *) System of linear equations has been solved with NumPy/SciPy Linear Algebra solve().
6654 *) Logs show how well the reconstructed polynomial closely approximates the original polynomial.
6655 *) Error locator polynomial E is degree 1 and Numerator Q is of degree = number of points thus yielding Q/E=P (recons
6656 *) Special case is natural language text with errors and a polynomial can be reconstructed from ordinal values of uni
6657
6658
6659 368. (FEATURE-DONE) Berlekamp-Welch Algorithm implementation - update for text message decoding - 27 January 2017
6660
6661 *) Using unicode values for ordinals with ord() and inverting with chr() causes overflow errors in SciPy/NumPy
6662 Linear Algebra Equation solver (solve()) because evaluating polynomials for large messages creates huge numbers
6663 *) Hence unicode has been replaced with a simple dictionaries - alphanumeric to numeric values and numeric to
6664 alphanumeric values.
6665 *) With above 2 dictionaries an example text message with error (garbled version of "thisissentence") is list
6666 decoded with a window of possible values for each letter positions.
6667 *) Logs show an approximate decoding of original message from message with error.
6668 *) Garbled text with error was created from a previous execution of Berlekamp-Welch algorithm.
6669
6670
6671 369. (THEORY) KRW Conjecture, KW relations, Majority Voting Circuit Composition - 30 January 2017 and 31 January 2017
6672
6673 Majority Voting Circuit for P(Good) binomial series RHS is a boolean circuit composition of NC Majority voting circui
6674 Voter Decision Functions for each voter variable input to Majority function defined as:
6675     Maj(m) + Voter(n) = Maj(Voter1(x1,x2,...,xn),Voter2(x1,x2,...,xn),...,Voterm(x1,x2,...,xn)).
6676 Assumption is Voter Decision Functions can be exactly learnt in Angluin Exact Learning model i.e Voters can have zero
6677 KRW Conjecture for boolean formula composition implies Depth(f+g) ~ Depth(f) + Depth(g) for composition f+g of two bc
6678 (fanout 1) f and g. Applying KRW conjecture to Maj(m) + Voter(n) Majority voting composition:
6679     Depth(Maj(m) + Voter(n)) ~ Depth(Maj(m)) + Depth(Voter(n))
6680 where m is the number of voters and n is the number of variables per voter decision function.
6681
6682 KW relations R(f) for a function f imply Depth(f) = CommunicationComplexity(R(f)).
6683 Karchmer-Wigderson relations for the composition are the following:
6684
6685 R(Maj,Voter):
6686
6687     Alice: x in Inverse(Maj + Voter)(0)
6688     Bob: y in Inverse(Maj + Voter)(1)
6689     Find xi and yi such that x != y
6690
6691 Depth(Maj + Voter) = CommunicationComplexity(R(Maj,Voter))
6692 Thus Majority voting circuit composition is a KW relation.
6693 There is an equivalent notion of Universal relation U(n) for KW relation defined as:
6694     Alice: x in {0,1}^(n)
6695     Bob: y in {0,1}^(n)
6696     Find xi and yi such that x != y
6697
6698 Result in 369.2 prove a lowerbound:
6699     Depth(g+U(n)) = CommunicationComplexity(R(g,U(n))) >= log L(g) + n - O(m*logm/n) where L(g) is the formula si

```

6700 If g is Majority function and U(n) is individual voter decision function, depth of composition of Majority and Voter
6701 D(Maj + Voter) = CommunicationComplexity(R(Maj,Voter)) $\geq \log L(\text{Majority}) + n - O(m \cdot \log m / n)$
6702 But formula size of Majority is $O(m^{5.3})$ implying depth of Majority+VoterDecisionFunction composition is:
6703 D(Maj + Voter) = CommunicationComplexity(R(Maj,Voter)) $\geq 5.3 \cdot \log m + n - O(m \cdot \log m / n)$
6704 Thus depth of Majority voting circuit for P(Good) RHS is lowerbounded by a function of number of voters and number of
6705
6706 369.1 prove a result which is an extension of 356.8:
6707 If a class C is exactly learnable in polynomial time, DTIME($n^{\omega(1)}$) is not in C. In mistake bounded learning mode
6708
6709 Exact Learning implies zero error on both sides of P(Good) binomial series. Assuming all boolean function are exactly
6710
6711 Let number of voter decision functions with goodness $x_i = m(x_i)$. Thus $N = m(x_1) + m(x_2) + m(x_3) + \dots + m(x_n)$
6712 Expected goodness of a PRG choice is:
6713 $\frac{1}{N} \cdot \sum m(x_i) = (x_1 \cdot m(x_1) + x_2 \cdot m(x_2) + x_3 \cdot m(x_3) + \dots + x_n \cdot m(x_n)) / N$
6714 When all voter functions have goodness 1 then PRG choice in LHS of P(good) has goodness 1.
6715
6716 Similarly, exact learning implies all voter decision functions are 100% perfect with zero-error in LHS. Binomial seri
6717
6718 Usual process of high level human learning vis-a-vis boolean function learning is bottom-up. Atomic concepts are lear
6719
6720 Hypothetical exact learner for 3SAT - NP voter decision functions :
6721 -----
6722 Given a truth table of size $n \cdot 2^n$ for n variables with truth values:
6723 *) Find a set of binary strings, satisfying truth values 1
6724 *) Construct a DNF for complement of the previous set
6725 *) Complement the DNF to get CNF for original set
6726
6727 Example - For following truth table, to construct CNF for satisfying assignments {000, 001, 011, 101, 110}:
6728 -----
6729

x1	x2	x3	truthvalue	complement
0	0	0	1	0
0	0	1	1	0
0	1	0	0	1
0	1	1	1	0
1	0	0	0	1
1	0	1	1	0
1	1	0	1	0
1	1	1	0	1

6730
6731
6732
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6736
6737
6738
6739
6740 DNF for complement set {010,100,111} is:
6741 $\neg x_1 \neg x_2 \neg x_3 + \neg x_1 \neg x_2 x_3 + x_1 \neg x_2 x_3$
6742 and the CNF learnt is complement of DNF:
6743 $(x_1 + \neg x_2 + x_3)(\neg x_1 + x_2 + x_3)(\neg x_1 + \neg x_2 + \neg x_3)$
6744 with satisfying assignments {000, 001, 011, 101, 110}
6745
6746 This exact learner requires $O(2^n)$ time which is exponential in number of variables.
6747
6748 369.6 describes an algorithm (CDNF) to learn any boolean functions in time polynomial in number of variables, its DNF
6749
6750 References:
6751 -----
6752 369.1 Exact Learning implies Derandomization (i.e. P=BPP) and Mistake bound learning - [KlivansKothariOliveira] - ht
6753 369.2 KRW Conjecture, KW relations and Lowerbound for Depth of Boolean Circuit Composition - [GavinskyMeirWeinsteinWi
6754 369.3 Generalization of Spira's Theorem - <https://www.cs.utexas.edu/users/panni/spira.pdf> - Spira's theorem transform
6755 369.4 Depth Hierarchy Theorem - [RossmanServedioTan] - Theorem 1 - <https://arxiv.org/pdf/1504.03398v1.pdf> - Circuit c
6756 369.5 Formula size of Majority function - [Valiant] - <http://www.sciencedirect.com/science/article/pii/01966774849001>
6757 369.6 Exact Learning of Boolean Functions from Monotone Theory - [Nader H. Bshouty] - <http://www.cs.technion.ac.il/~t>
6758 369.7 BPEXP is believed to collapse to EXP - if P=BPP then BPEXP=EXP (but converse BPEXP=EXP implying P=BPP is not kr
6759 369.8 From [Klivans-Fortnow] result mentioned in 369.1, if class EXP is efficiently PAC learnable with membership que
6760 contradicting BPEXP=EXP by homogeneous voter Condorcet Jury Theorem BPEXP circuit derandomization mentioned in 401. E
6761
6762 -----
6763 370. (FEATURE-DONE) An experimental special case k-CNF SAT Solver algorithm implementation - 31 January 2017
6764 -----
6765 Algorithm:
6766 -----
6767 *) Create a k-DNF from k-CNF input by negating literals in all clauses of k-CNF
6768 *) Binary encode the clauses of k-DNF into set of binary strings of length n where n is number of variables
6769 *) Compute the complement of the previous binary encoded set from set of 2^n binary strings
6770 *) These are satisfying assignments
6771 *) Presently requires all literals in each CNF clause
6772 *) Implemented for simulation of a Majority Voting with Voter SATs
6773
6774 -----
6775 371. (THEORY) Majority Boolean Function, Sensitivity, Roth's estimate and 2-Coloring/Complement Functions of Sequence
6776 1 February 2017 - related to 24,338 - Important draft updates to <https://arxiv.org/pdf/1106.4102v1>
6777 -----
6778 Boolean Majority Function finds the majority binary value of input binary string of length n. Any binary string of le
6779 considered as 2-coloring of bit position integers with corresponding complement functions for each color: $f(x)$ is for
6780 $g(x)$ is for 0s colored blue. For example, 1001011 is a 2-colored sequence with red (1) in bit positions 1,4,6,7 and b

```

6781 2,3,5. Complement functions for this bit position binary coloring are defined as:
6782   f(1)=1
6783   f(2)=4
6784   f(3)=6
6785   f(4)=7
6786 and
6787   g(1)=2
6788   g(2)=3
6789   g(3)=5
6790 Naturally, arithmetic progressions and monochromatic arithmetic progressions on these bit positions can be defined. Di
6791 difference between number of colored integers in an arithmetic progression. Roth's estimate which is the minimum(max
6792 for all possible colorings (i.e all possible binary strings) is  $\geq N^{(1/4+\epsilon)}$ . For majority function 2-coloring,
6793 the difference between number of 0s and 1s in the input to majority function with probability equal to natural densit
6794    $|f(x)| = \text{number of 1s} = [N + N^{(1/4+\epsilon)}]/2$  if majority function outputs 1
6795    $|g(x)| = \text{number of 0s} = [N - N^{(1/4+\epsilon)}]/2$  if majority function outputs 1
6796 and vice versa if majority function outputs 0. For previous example, majority is 1 and :
6797    $|f(x)| = \text{number of 1s} = [7 + 7^{0.25}]/2 = 4.313288 \sim 4$ 
6798    $|g(x)| = \text{number of 0s} = [7 - 7^{0.25}]/2 = 2.6867 \sim 3$ 
6799 Sensitivity of Majority function is number of bits to be flipped to change the outcome which is nothing but the discr
6800
6801 -----
6802 372. (FEATURE-DONE) Reinforcement Learning - ThoughtNet based Recommender Systems Implementation Update - 2 February
6803
6804 *) Recursive Gloss Overlap classifier disambiguation has been updated to invoke NLTK lek algorithm function() with c
6805 choose between PyWSD lek implementation and best_matching_synset() primitive disambiguation native implementation
6806 *) New usecase shopping cart example with book reviews has been added
6807 *) Fixed a major bug in RecursiveGlossOverlap Classifier in definition graph construction : Edges for all lemma names
6808
6809 -----
6810 373. (FEATURE-DONE) Recursive Gloss Overlap classifier update - 3 February 2017
6811 -----
6812 Uncommented NetworkX matplotlib graph plotting to get a graph for a sample document definition graph. Logs and PNG fi
6813
6814 -----
6815 374. (THEORY and FEATURE-DONE) CNFSAT solver update - polynomial time approximation - 5 February 2017
6816 -----
6817 Solves CNFSAT by a Polynomial Time Approximation scheme:
6818   - Encode each clause as a linear equation in n variables: missing variables and negated variables are 0, other
6819   - Solve previous system of equations by least squares algorithm to fit a line
6820   - Variable value above 0.5 is set to 1 and less than 0.5 is set to 0
6821   - Rounded of assignment array satisfies the CNFSAT with high probability
6822 Essentially each CNF is represented as a matrix A and solved by  $AX=B$  where X is the column vector of variables and B
6823
6824 -----
6825 375. (FEATURE-DONE) Java Spark Streaming - Generic Stream Receiver Implementation - 6 February 2017
6826 -----
6827 Spark Streaming Java implementation to receive generic stream of unstructured text data from any URL and Sockets has
6828 NeuronRain AsFer java/bigdata_analytics/. It is based on Spart 2.1.0 + Hadoop 2.7 single node cluster. Following are
6829
6830 *) Oracle Java 8 compiler and runtime and PATH set to it
6831 *) export CLASSPATH=/home/shrinivaasanka/spark-2.1.0-bin-hadoop2.7/jars/spark-streaming_2.11-2.1.0.jar:./home/shrin
6832 *) Compiled as: javac SparkGenericStreaming.java
6833 *) JAR packaging of SparkGenericStreaming*.class : jar -cvf sparkgenericstreaming.jar *class
6834 *) Example Spark submit commandline for 2 local threads (2 cores) and data streamed from twitter :
6835 /home/shrinivaasanka/spark-2.1.0-bin-hadoop2.7/bin/spark-submit --class SparkGenericStreaming --master local[2] spark
6836
6837 Spark Streaming Java implementation complements Streaming Abstract Generator Python native abstraction implemented in
6838
6839 -----
6840 376. (FEATURE-DONE) Java Spark Streaming for Generic data - Jsoup ETL integration - 7 February 2017
6841 -----
6842 *) Jsoup HTML parser has been imported into SparkGenericStreaming.java and a very basic Extract-Transform-Load is
6843 performed on the URL passed in with a special boolean flag to use Jsoup
6844 *) Jsoup connects to URL and does a RESTful GET of the HTML, extracts text from HTML and stores the text in Spark RDD
6845 *) receive() is periodically invoked and word count is computed
6846 *) foreachRDD() is invoked on the DStream to iterate through all words in DStream.
6847 *) foreach() invokes a lambda function to print the word text
6848 *) Logs for this have been added to spark_streaming/testlogs/
6849
6850 spark-submit commandline requires additional classpath to jsoup .jar with --jars option as below:
6851 /home/shrinivaasanka/spark-2.1.0-bin-hadoop2.7/bin/spark-submit --class SparkGenericStreaming --master local[2] --jar
6852
6853 -----
6854 377. (THEORY and FEATURE-DONE) Approximate SAT solver update - 8 February 2017 - related to 374
6855 -----
6856 Updated CNFSATSolver.py to create set of random 3CNFs and verify if the least squares assignment is satisfied. Preser
6857
6858 References:
6859 -----
6860 377.1 PCP theorem and Hardness of Approximation - http://www.cs.jhu.edu/~scheideler/courses/600.471\_S05/lecture\_9.pdf
6861 377.2 PCP theorem and Hardness of Approximation - http://pages.cs.wisc.edu/~dieter/Courses/2008s-C5880/Scribes/lectur

```

6862
6863
6864 378. (FEATURE-DONE) Java Spark Streaming Generic Receiver update - 9 February 2017
6865
6866 *) Objectified the SparkGenericStreaming more by moving the SparkConf and JavaStreamingContext into
6867 class private static data.
6868 *) new method SparkGenericStreamingMain() instantiates the Spark Context and returns the JavaPairDStream<String,Integ
6869 *) main() static method instantiates SparkGenericStreaming class and receives wordCounts JavaPairDStream from SparkGe
6870 *) Spark JavaStreamingContext output operations are invoked by start() and print actions by lambda expressions.
6871 *) SparkConf and JavaStreamingContext variables have to be static because Not Serializable exceptions are thrown othe
6872 *) sparkgenericstreaming.jar has been repackaged by recompilation.
6873
6874
6875 379. (FEATURE-DONE) Spark Streaming Java Update - Java Bean DataFrame(Dataset) creation, Hive Metastore support and p
6876 DataFrame to Hive and as a Parquet file - 10 February 2017
6877
6878 *) New JavaSparkSingletonInstance class for singleton Spark Context has been added.
6879 *) New Java Bean Word.java has been added for creating DataFrame from JavaRDD iterable
6880 *) DataFrame has been persisted to filesystem as .parquet file in overwrite mode of DataFrameWriter
6881 *) DataFrame has also been persisted to Hive MetaStore db which Spark supports (Shark SQL) with saveAsTable()
6882 *) SparkGenericStreaming has been rewritten to do transformations on words JavaRDD iterable with VoidFunction() in
6883 2-level nested iterations of foreachRDD() and foreach()
6884 *) map() transformation for each row in JavaRDD throws a null pointer exception and inner call() is never invoked.
6885 *) This has been remedied by replacing map() with a foreach() and storing the rows in each RDD in an ArrayList
6886 *) With Hive MetaStore + Shark integration, Streaming_AbstractGenerator.py abstraction now has access to Java Spark S
6887 because it already supports Hive via thrift and NeuronRain now has ability to analyze any realtime or batch unstructu
6888 *) Primitive ETL to just scrape words in URL text sufficiently tracks trending topics in social media.
6889 *) Hive metastore db, Spark warehouse data have been committed and Logs for this has been added to testlogs/
6890 *) sparkgenericstreaming.jar has been repackaged with recompilation
6891 *) Updated spark-submit commandline: /home/shrinivaasanka/spark-2.1.0-bin-hadoop2.7/bin/spark-submit --class SparkGen
6892 *) Updated CLASSPATH: export CLASSPATH=/home/shrinivaasanka/spark-2.1.0-bin-hadoop2.7/jars/scala-reflect-2.11.8.jar:/
6893
6894
6895 380. (THEORY) Machine Translation, Recursive Gloss Overlap Graphs in different Natural Languages and Graph Homomorphi
6896 - related to 178
6897
6898 Machine Translation is equivalent to graph homomorphism between 2 recursive gloss overlap graphs of a text in 2 natur
6899 homomorphism f for translation is defined as:
6900 if (u,v) is in E(G1) then (f(u),f(v)) is in E(G2)
6901 for recursive gloss overlap graphs G1 and G2 for languages L1 (e.g. English) and L2 (e.g Tamizh) constructed from res
6902 In previous definition, u and v are two words in natural language L1 and f(u) and f(v) are two words in natural langu
6903 This relaxes the isomorphism requirement mentioned in 178. Set of all digraphs G such that there is a homomorphism fr
6904 denoted by L(H). Guessing the set of digraphs G for a digraph H implies finding set of all translations for a text fr
6905 languages to another natural language. This guessing problem is known by Dichotomy Conjecture to be either in P or NP
6906
6907
6908 381. (FEATURE-DONE) Approximate SAT solver update - 14 February 2017
6909
6910 *) Changed number of variables and clauses to 14 and 14 with some additional debug statements.
6911 *) After 4000+ iterations ratio of random 3SAT instances satisfied is: ~70%
6912
6913
6914 382. (FEATURE-DONE) Java Spark Streaming with NetCat WebServer update and some analysis on HiveServer2+Spark Integrat
6915
6916 *) Rewrote SparkGenericStreaming.java mapreduce functions with Spark 2.1.0 + Java 8 lambda functions
6917 *) Enabled Netcat Socket streaming boolean flag instead of URL socket with Jsoup
6918 *) With above changes (and no HiveServer2), socket streaming receiver works and Hive saveAsTable()/Parquet file savin
6919 *) HiveServer2 was enabled in Spark Conf by adding hive-site.xml in spark/conf directory. (Two example hive-site.xml(
6920 committed to repository.)
6921 *) Spark 2.1.0 was started with hive-site.xml to connect to HiveServer2 2.1.1. This resulted in 2 out of heapspace er
6922 in testlogs/ with exception "Error in instantiating HiveSessionState".
6923 *) Such OOM errors with HiveServer2 and Spark have been reported earlier in Apache JIRA. Instead of TTransport, Frame
6924 tried which caused "Frame size exceeds maximum frame size" errors. SASL was also disabled in hive-site.xml.
6925 *) Reason for such OOM errors in HiveServer2 seems to be heavy memory footprint of HiveServer2 and Spark together and
6926 for both cores. Might require a high-end server with large RAM size so that heapspace is set to atleast 8GB. HiveServ
6927 memory intensive application. Also Spark only supports Hive 1.2.1 and not Hive 2.1.1 which could be the reason.
6928 *) Increasing Java Heap space in spark config file (spark.executor.memory and spark.driver.memory) also did not have
6929 *) Setting HADOOP_HEAPSIZE also did not have effect. OOM error occurs while instantiating HiveSessionState and bootst
6930 (get_all_databases). Isolated beeline CLI connection works though with HiveServer2.
6931 *) Hence presently Spark Streaming works with Spark provided metastore_db Hive Support and Parquet file support.
6932 *) testlogs/ have stream processing logs for NetCat (NC) webserver.
6933
6934
6935 383. (FEATURE-DONE) Spark Version Upgrade for Recursive Gloss Overlap Graph Intrinsic merit and Discrete Hyperbolic F
6936 Implementations - 21 February 2017
6937
6938 *) Re-executed Interview Algorithm and Factorization Spark Cloud implementations with Spark 2.1.0 and Cython optimiza
6939 Gloss Overlap Graph construction
6940 *) Earlier these were benchmarked with Spark 1.5.x
6941 *) Added debug statements in python-src/DiscreteHyperbolicFactorizationUpperbound_Bitonic_Spark.py and file locations
6942 committed to python-src/testlogs and python-src/InterviewAlgorithm/testlogs


```

7024 Previous composition tree is done for each Markov Chain Random Walk on the Definition Graph. Difference between compc
7025
7026 Advantage of Random Walks is it mimicks the randomness of deep learning in human text comprehension. Typical visual c
7027
7028 References:
7029 -----
7030 386.1 Random Walks Survey - http://www.cs.elte.hu/~lovasz/erdos.pdf
7031 386.2 Random Walks on Weighted Directed Graphs - http://www.cs.yale.edu/homes/spielman/eigs/lect7.pdf
7032
7033 -----
7034 387. (FEATURE-DONE) Java Spark Generic Streaming and Streaming Abstract Generator Integration - 27 February 2017
7035 -----
7036 *) Enabled URLSocket in Spark Generic Streaming and crawled an example facebook and twitter
7037 streaming data stored into Parquet files and Spark metastore
7038 *) Added Spark Streaming Data Source and Parquet Data Storage to Streaming_AbstractGenerator.py
7039 and updated iterator to read DataFrames from word.parquet Spark Streaming storage.
7040 *) Spark DataFrames are iterated by accessing word column ordinal and yielded to any application of
7041 interest.
7042 *) As an example Streaming HyperLogLogCounter implementation has been updated to read from Spark
7043 Parquet streaming data storage and cardinality is computed
7044 *) Example Spark Generic Streaming logs with URLs and HyperLogLogCounter with Spark Parquet
7045 data storage have been added to testlogs in python-src and java-src/bigdata_analytics/spark_streaming/testlogs
7046 *) Thus an end-to-end Java+Spark+Python streaming ETL pipeline has been implemented where:
7047     - Extract is done by Jsoup crawl
7048     - Transform is done by Spark RDD transformations
7049     - Store is done by Spark Hive and Parquet storage
7050     - Load is done by Streaming Abstract Generator iterator/facade pattern
7051 *) Streaming_HyperLogLogCounter.py instantiates SparkSession from pyspark.sql. Usage of SparkSession requires executi
7052
7053 -----
7054 388. (FEATURE-DONE) Streaming Algorithms Implementations for Spark Streaming Parquet Data Storage - 28 February 2017
7055 -----
7056 *) All Streaming_<algorithm> implementations have been updated to have Spark Streaming
7057 Parquet file storage as input generators.
7058 *) New Streaming_SocialNetworkAnalysis.py file has been added to do sentiment analysis for
7059 Streaming Data from Spark Parquet file storage
7060 *) Streaming_AbstractGenerator.py has been updated to filter each Spark Parquet DataFrame to remove
7061 grammatical connectives and extract only keywords from streamed content
7062 *) Logs for all Streaming_<algorithm>.py and Streaming_SocialNetworkAnalysis.py executed against
7063 Spark Streaming Parquet data have been committed to testlogs/
7064 *) Streaming_SocialNetworkAnalysis.py presently iterates through word stream generated by
7065 Streaming_AbstractGenerator.py and does Markov Random Fields Clique potential sentiment analysis.
7066 *) Streaming_AbstractGenerator.py Spark Parquet __iter__() clause presently returns word stream which
7067 can be optionally made to return sentences or phrases of specific length
7068 *) All python streaming implementations instantiating Streaming_AbstractGenerator.py have to be executed with $SPARK_
7069
7070 -----
7071 389. (FEATURE-DONE) Major rewrite of BackPropagation Implementation for arbitrary number of Neuron input variables la
7072
7073 *) BackPropagation algorithm code has been rewritten for arbitrary number of input layer, hidden layer and output lay
7074 *) Some Partial Differential Equations functions have been merged into one function.
7075 *) This was executed with 6 variable input layer neuron, 6 variable hidden layer and 6 variable output layer with 2*6
7076 for each of 72 activations.
7077 *) Logs for this have been committed to testlogs/
7078 *) For 100000 iterations, error tapers to ~10^-29 as below
7079
7080 Error after Backpropagation- iteration : 99998
7081 1.05827458078e-29
7082 Layers in this iteration:
7083 #####
7084 Input Layer:
7085 #####
7086 [0.23, 0.11, 0.05, 0.046, 0.003, 0.1]
7087 #####
7088 Hidden middle Layer:
7089 #####
7090 [0.07918765738490302, 0.17639329000539292, 0.3059104560477687, 0.06819897810162112, 0.13596389556531566, 0.1809236742
7091 #####
7092 Output Layer:
7093 #####
7094 [0.2999999999999977, 0.53, 0.1100000000000039, 0.0900000000000002, 0.01000000000004578, 0.2099999999999999]
7095 Weights updated in this iteration:
7096 [0.048788506679748, 0.11426171324845727, 0.24603459114714846, 0.0795780558315572, 0.17784209754093078, 0.189016659729
7097 Recomputing Neural Network after backpropagation weight update
7098 Error after Backpropagation- iteration : 99999
7099 1.05827458078e-29
7100 Layers in this iteration:
7101 #####
7102 Input Layer:
7103 #####
7104 [0.23, 0.11, 0.05, 0.046, 0.003, 0.1]

```

```

7105 #####
7106 Hidden middle Layer:
7107 #####
7108 [0.07918765738490302, 0.17639329000539292, 0.3059104560477687, 0.06819897810162112, 0.13596389556531566, 0.1809236742
7109 #####
7110 -----
7111 -----
7112 -----
7113 390. (FEATURE-DONE) Convolution Network Final Neuron Layer Integrated with BackPropagation Implementation- 3 March 26
7114 -----
7115 *) New python module has been added to repository to invoke BackPropagation algorithm
7116 implementation in final neuron layer of convolution network.
7117 *) This creates a multilayer perceptron from maxpooling layer variables as input layer and
7118 backpropagates for few iterations to do weight updates.
7119 *) Maxpooling layer is a matrix of 5*5=25 variables. With 25 variable input layer, backpropagation
7120 is done on 25*25*2=1250 activation edges with weights(25 inputs * 25 hidden + 25 hidden * 25 outputs).
7121 *) Logs for this have been added to testlogs/
7122 *) Presently expected output layer has been hardcoded to some constant
7123
7124 -----
7125 391. (THEORY) Prime-Composite Complementation/2-coloring, Riemann Zeta Function and Sum of Eigenvalues - Elementary A
7126 - related to 19, 24, 319, 323, 338, 371
7127 -----
7128 Special case of complementation/2-coloring is prime-composite coloring where set of natural numbers is 2-colored as p
7129 Here terminology of complementation and 2-coloring is used interchangeably. But complementation is a generic notion f
7130 reals too. Riemann Zeta Function and truth of Riemann Hypothesis imply a pattern in distribution of primes and hence
7131 coloring. Thus Riemann Zeta Function is a 2-coloring scheme for set of natural numbers.
7132
7133 Let  $q^s + q^{(1-s)} = v$  be an eigenvalue of a graph where  $s$  is a complex exponent ( $s=a+ib$ ). It can be written as:
7134 
$$q^{2s} + q = vq^{(a+ib)}$$

7135 
$$q^{2a}q^{2ib} + q = vq^{a+ib}$$

7136 
$$q^{2a}q^{2ib} + q = vq^a[e^{ib\log q}]$$
 by rewriting  $q^{ib} = e^{ib\log q}$ 
7137 
$$q^{2a}[\cos(2b\log q) + i\sin(2b\log q)] + q = vq^a[\cos(b\log q) + i\sin(b\log q)]$$

7138
7139 Equating Re() and Im():
7140 
$$q^{2a}[\cos(2b\log q)] + q = vq^a[\cos(b\log q)]$$

7141 
$$q^{2a}[\sin(2b\log q)] = vq^a[\sin(b\log q)]$$

7142 Ratio of Re() and Im() on both sides:
7143 
$$\frac{q^{2a}[\sin(2b\log q)]}{q^{2a}[\cos(2b\log q)] + q} = \frac{vq^a[\sin(b\log q)]}{vq^a[\cos(b\log q)]}$$

7144
7145 
$$\frac{q^{2a}[2*\sin(b\log q)*\cos(b\log q)]}{q^{2a}[\cos(2b\log q)] + q} = \frac{[\sin(b\log q)]}{[\cos(b\log q)]}$$

7146
7147 
$$\frac{q^{2a}[2*\cos(b\log q)*\cos(b\log q)]}{q^{2a}[\cos(2b\log q)] + q} = q^{2a}[\cos(2b\log q)] + q$$

7148
7149 
$$\frac{q^{2a}[2*\cos(b\log q)*\cos(b\log q)]}{q^{2a}[\cos(2b\log q)] + q} = q^{2a}[\cos(b\log q)*\cos(b\log q) - \sin(b\log q)*\sin(b\log q)] + q$$

7150
7151 
$$q^{2a}[\cos(b\log q)*\cos(b\log q) + \sin(b\log q)*\sin(b\log q)] = q$$

7152
7153 
$$q^{2a} = q \Rightarrow a = 0.5$$

7154
7155 When  $s=0.5$  with no imaginary part and  $q+1$  is regularity of a graph,  $v = 2*\sqrt{q}$  and corresponding graph is a  $q+1$  re
7156
7157 [This is already derived in:
7158 https://sites.google.com/site/kuja27/RamanujanGraphsRiemannZetaFunctionAndIharaZetaFunction.pdf,
7159 https://sites.google.com/site/kuja27/RZFAndIZF\_250ctober2014.pdf,
7160 http://sourceforge.net/p/asfer/code/HEAD/tree/python-src/ComplFunction\_DHF\_PVsNP\_Misc\_Notes.pdf]
7161
7162 Let  $H = \{G1, G2, G3, \dots\}$  be an infinite set of graphs with eigenvalues  $1^s + 1^{(1-s)}$ ,  $2^s + 2^{(1-s)}$ ,  $3^s + 3^{(1-s)}$ , ...
7163
7164 Sum of these eigenvalues for infinite set of graphs has following relation to Riemann Zeta Function for  $s=w+1$ :
7165 
$$\sum_{q=1}^{\infty} (q^s + q^{(1-s)}) = [1 + 1/2^w + 1/3^w + \dots] + [1 + 2^{(w+1)} + 3^{(w+1)} + \dots] = \text{RiemannZetaFunction} + [1 + 2^{(w+1)} + 3^{(w+1)} + \dots]$$

7166
7167 
$$\sum_{q=1}^{\infty} (q^s + q^{(1-s)}) - [1 + 2^{(w+1)} + 3^{(w+1)} + \dots] = \text{RiemannZetaFunction}$$

7168
7169 Thus Riemann Zeta Function is written as difference of sum of eigenvalues for an infinite set of graphs and another i
7170 Hermitian Real Symmetric matrices have real eigenvalues which is true for undirected graphs. For directed graphs, eig
7171
7172 References:
7173 -----
7174 391.1 Complex Analysis - [Lahs Alfors] - Page 213 - Product Development, Riemann Zeta Function and Prime Numbers
7175 391.2 Honeycombs and Sums of Hermitian Matrices - http://www.ams.org/notices/200102/fea-knutson.pdf
7176
7177 -----
7178 392. (FEATURE-DONE) DeepLearning (ConvolutionNetwork-BackPropagation) JPEG files with Python Imaging Library (PILlow)
7179
7180 -----
7181 *) Added import of PIL Image library to open any image file and convert into a matrix in Integer mode
7182 *) This matrix is input to Convolution and BackPropagation code
7183
7184
7185

```

```

7186 *) Logs of Convolution and BackPropagation for sample images have been committed to testlogs/
7187
7188
7189 393. (FEATURE-DONE) DeepLearning (ConvolutionNetwork-BackPropagation) tobit() update - 7 March 2017
7190
7191 *) Updated python-src/DeepLearning_ConvolutionNetwork_BackPropagation.py tobit() function to map each pixel to a deci
7192 *) Increased BackPropagation iteration to 100.
7193 *) Logs for this have been committed to testlogs/. With this final neurons for max pooling layer are sensitive to cha
7194
7195
7196 394. (FEATURE-DONE) DeepLearning (ConvolutionNetwork-BackPropagation) image_to_bitmatrix() update - 8 March 2017
7197
7198 *) Refactored the tobit() function - moved it to a new directory image_pattern_mining and reimplemented it with a new
7199 image_to_bitmatrix() function in ImageToBitMatrix.py by enumerating through the pixel rows and applying map(tobit)
7200 *) This removed the opaqueness related 255 appearing for all pixels in bitmap.
7201 *) Each pixel is multiplied by a fraction. Mapping it to binary digits 0,1 based on [0-127],[128-255] intervals for p
7202 does not work well with BackPropagation of MaxPooling in Convolution Network. Instead multiples of a small fraction n
7203 MaxPooling layer quite receptive to changes in image pixel values.
7204 *) Added few handwriting recognition example images for numbers 1(two fonts),2 and 8.
7205 *) Logs for this have been committed to testlogs/
7206
7207 Following are Maxpooling Neurons
7208
7209 Final Layer of Inference from Max Pooling Layer - BackPropagation on Max Pooling Layer Neurons
7210 Inference from Max Pooling Layer - Image: [0.1452950826564989, 0.15731736449115244, 0.16984767785665972]
7211 Inference from Max Pooling Layer - Image: [0.1492088863234688, 0.16193600589418844, 0.17528092024601222]
7212 Inference from Max Pooling Layer - Image: [0.13197897244871004, 0.1417448800619895, 0.15171424525284838]
7213 Inference from Max Pooling Layer - Image: [0.14007345008310818, 0.15118749472569865, 0.16267822705412283]
7214 Inference from Max Pooling Layer - Image: [0.07847441088145349, 0.0807616625716103, 0.08303607840796547]
7215 Inference from Max Pooling Layer - Image: [0.08983732685398557, 0.09365789540391084, 0.09744765711798722]
7216 Inference from Max Pooling Layer - Image: [0.0903328782140764, 0.09421672093823663, 0.09806798136073994]
7217 Inference from Max Pooling Layer - Image: [0.08761036574911765, 0.09113121170496671, 0.09462405037074482]
7218 ('Inference from Max Pooling Layer - Example 11:', [0.1619896774094416, 0.1615169723530323, 0.15009965578039716])
7219 ('Inference from Max Pooling Layer - Example 12:', [0.14303879829783814, 0.12068614560924568, 0.07211705852669059])
7220 ('Inference from Max Pooling Layer - Example 21:', [0.1932801269861012, 0.11587916253160746, -0.007889615456070018])
7221 ('Inference from Max Pooling Layer - Example 22:', [0.17605214289097237, 0.19326380725531284, 0.2114152778184319])
7222 ('Inference from Max Pooling Layer - Example 3:', [0.062097695970929206, 0.062097695970929206, 0.062097695970929206])
7223 ('Inference from Max Pooling Layer - Example 41:', [0.2976324086103368, 0.32891470561393965, 0.34986397693929844])
7224 ('Inference from Max Pooling Layer - Example 42:', [0.22669904395788065, 0.26336097548290116, 0.3065443950445386])
7225 ('Inference from Max Pooling Layer - Example 51:', [0.11935155170571034, 0.12477637373255022, 0.12911872514904305])
7226 ('Inference from Max Pooling Layer - Example 52:', [0.12675869649313706, 0.12051203261825084, 0.10578392639393523])
7227
7228 Previous logs are grep-ed from testlogs/. Handwritten Numeral recognitions (with high noise) are done in following Ma
7229 [Number 1 - Font 1] Inference from Max Pooling Layer - Image: [0.07847441088145349, 0.0807616625716103, 0.08303607846
7230 [Number 1 - Font 2] Inference from Max Pooling Layer - Image: [0.08983732685398557, 0.09365789540391084, 0.0974476571
7231 [Number 2] Inference from Max Pooling Layer - Image: [0.0903328782140764, 0.09421672093823663, 0.09806798136073994]
7232 [Number 8] Inference from Max Pooling Layer - Image: [0.08761036574911765, 0.09113121170496671, 0.09462405037074482]
7233
7234 Contrasting this with bitmap numerals inscribed in 2 dimensional arrays (with low noise), similar elements have close
7235 [Number 0 - Font 1] ('Inference from Max Pooling Layer - Example 11:', [0.1619896774094416, 0.1615169723530323, 0.150
7236 [Number 0 - Font 2] ('Inference from Max Pooling Layer - Example 12:', [0.14303879829783814, 0.12068614560924568, 0.0
7237 [Number 8 - Font 1] ('Inference from Max Pooling Layer - Example 21:', [0.1932801269861012, 0.11587916253160746, -0.0
7238 [Number 8 - Font 2] ('Inference from Max Pooling Layer - Example 22:', [0.17605214289097237, 0.19326380725531284, 0.2
7239 [Null pattern] ('Inference from Max Pooling Layer - Example 3:', [0.062097695970929206, 0.062097695970929206, 0.06209
7240 [Letter X - Font 1] [('Inference from Max Pooling Layer - Example 41:', [0.2976324086103368, 0.32891470561393965, 0.3
7241 [Letter X - Font 2] ('Inference from Max Pooling Layer - Example 42:', [0.22669904395788065, 0.26336097548290116, 0.3
7242 [Number 1 - Font 1] ('Inference from Max Pooling Layer - Example 51:', [0.11935155170571034, 0.12477637373255022, 0.1
7243 [Number 1 - Font 2] ('Inference from Max Pooling Layer - Example 52:', [0.12675869649313706, 0.12051203261825084, 0.1
7244
7245
7246 395. (THEORY) Coloring Real Numbers and Complement Functions - 8 March 2017 - related to 323, 338
7247
7248 So far equivalence of 2-coloring schemes and integer valued complement functions have been mentioned. Most generic pr
7249 is to find coloring schemes (or) functions which "complement" real and complex n-dimensional surfaces(i.e sets of val
7250 its complement g create a disjoint set cover of the real/complex planes). Ramsey theory pertains to coloring integer
7251 the problem of coloring the real line as minimum number of colors required to color the real line such that no two pe
7252 graph where two vertices a and b are adjacent iff distance between a and b on real line is in distance set. This is s
7253 of coloring compared to complementation and complement graphs representation mentioned in 338. For example, following
7254     f(0) = [1.0,1.11]
7255     g(0) = [1.12,1.23]
7256     f(1) = [1.24,1.30]
7257     g(1) = [1.31,1.68]
7258     f(2) = [1.69,2.0]
7259 has colored regions of length [0.11,0.11,0.06,0.37,0.31] and can be 2-colored with f and g. If the distance set is {0
7260 points 1.32 and 1.33 are 0.01 apart but have same color (belong to same function g). Similarly points 1.69 and 1.71 a
7261 have same color f. Thus complementation over reals relaxes the coloring conditions significantly. Coloring real line
7262 complementation with distance set requirement while Coloring integers is equivalent to complementation. Rather, distan
7263 complementation is of size 1 containing length of largest monochromatic streak - in previous example it is {0.37}.
7264
7265 References:
7266

```

```

7267 395.1 Coloring Real Line - [EggletonErdosSkilton] - http://ac.els-cdn.com/0095895685900395/1-s2.0-0095895685900395-ma
7268 395.2 Coloring Reals - http://webbuild.knu.ac.kr/~trj/HN.pdf
7269
7270
7271 396. (FEATURE-DONE) Deep Learning Recurrent Neural Network Gated Recurrent Unit (RNN GRU) Implementation - 9 March 26
7272
7273 *) This commit implements Gated Recurrent Unit algorithm (most recent advance in deep learning - published in 2014) w
7274 simplification of RNN LSTM by reducing number of gates (input, cell, forget, output are mapped to cell, reset, update
7275 *) Logs for this have been uploaded to testlogs/ showing convergence of gates and state.
7276
7277
7278 397. (FEATURE-DONE) Recursive Lambda Function Growth + Tensor Neuron (NTN) Intrinsic Merit - 13 March 2017 - related
7279
7280 *) This commit rewrites the Recursive Lambda Function Growth implementation by adding a new lambda function growth
7281 function.
7282 *) This new function creates a definition graph with Recursive Gloss Overlap algorithm from a text and computes all p
7283 *) For each such shortest path edges, an AVL lambda function composition balanced tree is grown (i.e every path is a
7284 *) Tensor Neuron Lambda Function is computed for each subtree root by following relation evaluated on a stack:
7285         function(operand1, operand2)
7286 where operand1, operand2 and function are successively popped from AVL composition tree stack representation
7287 *) Tensor Neuron triplet (operand1, function, operand2) is evaluated presently as maximum Wu-Palmer similarity of Syr
7288 *) Sum of tensor neuron weights for all random walks composition tree evaluation is printed as merit of the text.
7289 *) Logs for this have been committed to testlogs
7290
7291
7292 398. (FEATURE-DONE) Korner Entropy Intrinsic Merit for Recursive Gloss Overlap graphs - 14 March 2017 - related to 38
7293
7294 *) Implemented Korner Entropy intrinsic merit for Recursive Gloss Overlap graph.
7295 *) function korner_entropy() finds maximal independent sets for all vertices and chooses the minimum entropy such tha
7296 *) Logs for this have been committed to testlogs/
7297
7298 Previous two intrinsic merit measures - tensor neuron network and korner entropy - sufficiently quantify the complexi
7299
7300
7301 399. (FEATURE-DONE) Software Analytics update - 15 March 2017
7302
7303 *) Software Analytics Deep Learning code has been updated to include all Deep Learning implementations: RNN LSTM, RNN
7304 and ConvolutionNetwork+BackPropagation
7305 *) logs for this have been committed to software_analytics/testlogs/
7306
7307
7308 400. (USECASE) NeuronRain Usecases - Software (Log) Analytics and VIRGO kernel_analytics config - 16 March 2017 and 2
7309
7310 Software Analytics Deep Learning implementation in python-src/software_analytics/ sources its input variables - CPU%, 
7311
7312     If the CPU% is > 75% and Memory% > 75% and TimeDuration% > 75% then
7313         do a kernelwide overload signal
7314     else
7315         do nothing
7316
7317 Sigmoid function for this usecase is:
7318     sigma(4/9 * x1 + 4/9 * x2 + 4/9 * x3) where x1 = CPU%, x2 = Memory% and x3 = TimeDuration%
7319 which is 1 when all variables reach 75%.
7320
7321 Spark Streaming Log Analyzer ETLs htop data to .parquet files and Software Analytics code reads it, deep-learns above
7322
7323 An inverse of this usecase is to find the weights for x1,x2,x3 when system crashes. This requires a gradient descent
7324
7325
7326 401. (THEORY) Mechanism Design, Condorcet Jury Theorem, Derandomization, Gibbard-Satterthwaite Theorem and Designing
7327 - 27 March 2017 , 30 March 2017 ,31 March 2017, 18 April 2017 - related to 369 and all other P(Good) circuit related
7328
7329 Gibbard-Satterthwaite theorem prevents any Social Choice Function defined on atleast 3 elements from being non-dictat
7330
7331 A simple example of strategic/tactical voting and Gibbard-Satterthwaite theorem is given in http://rangevoting.org/Ir
7332
7333 This implies for more than 3 candidates, RHS of P(Good) series for majority voting can never converge because there i
7334
7335 Condorcet Jury Theorem mentioned in references below, is exactly the P(Good) binomial series summation and has been s
7336
7337 Corollary: From 129 and 369, depth of Majority voting circuit composition can be unbounded and if all voter social ch
7338
7339 If Majority Voting Circuit is in BPP, which is quite possible if number of voters is polynomial in number of variable
7340
7341 Locality Sensitive Hashing accumulates similar voters in a bucket chain. The social choice function is the distance f
7342     *) Locality Sensitive Hashing (LSH) for clustering similar voters who vote for same candidate
7343     *) Sorting the LSH and find the maximum size cluster (bucket chain)
7344
7345 References:
7346
7347 401.1 Mechanism Design, Convicting Innocent, Arrow and GibbardSatterthwaite Theorems - https://ocw.mit.edu/courses/el

```

7348 401.2 Electoral Fraud, Gibbard-Satterthwaite Theorem and its recent extensions on manipulative and strategic voting,
 7349 401.3 Most important point of this document (which I was searching for 11 years) - Condorcet Jury Theorem in Politica
 7350 "... Condorcet's Jury theorem applies to the following hypothetical situation: suppose that there is some
 7351 401.4 Strategic Voting and Mechanism Design - [VinayakTripathi] - <https://www.princeton.edu/~smorris/pdfs/PhD/Tripathi.pdf>
 7352 401.5 Condorcet Jury Theorem and OCR - Section 2 - <http://math.unipa.it/~grim/Jlamlouisa.PDF>
 7353 401.6 Condorcet Jury Theorem graph plots - <http://www.statisticalconsultants.co.nz/blog/condorcets-jury-theorem.html>
 7354 401.7 Probabilistic Aspects of Voting - Course Notes - www.maths.bath.ac.uk/~ak257/talks/Uugnaa.pdf - Condorcet Jury
 7355 401.8 Law of Large Numbers and Weighted Majority - [Olle Haggstrom, Gil Kalai, Elchanan Mossel] - <https://arxiv.org/abs/1302.0808>
 7356 401.9 Thirteen Theorems in search of truth - <http://www.socsci.uci.edu/~bgoelman/69%20Grofman-Owen-Feld-13%20theorems.pdf>
 7357 401.10 Margulies-Russo Formula and Condorcet Jury Theorem - <http://www.cs.tau.ac.il/~amnon/Classes/2016-PRG/Analysis-Lecture-1.pdf>
 7358 401.11 Percolation, Sharp Threshold in Majority, Condorcet Jury Theorem and later results, Influence, Pivotality - <http://www.maths.bath.ac.uk/~ak257/talks/Uugnaa.pdf>
 7359 401.12 Complexity Inclusion Graph - <https://www.math.ucdavis.edu/~greg/zooiology/diagram.xml> - BPEXP=EXP implies a sign
 7360
 7361 -----
 7362 402. (FEATURE-DONE) LSH Index implementation for NeuronRain AsFer Text and Crawled Web Documents Intrinsic Merit Rank
 7363 -----
 7364 *) This commit adds a Locality Sensitive Hashing based inverted index for scrapy crawled **HTML** website pages.
 7365 *) It is a derivative of LSH based similarity clustering implemented in `python-src/LocalitySensitiveHashing.py`
 7366 *) It has to be mentioned here that ThoughtNet is also an inverted index for documents with additional features (i.e.
 7367 classifier based than raw string similarity)
 7368 *) LSHIndex uses Redis Distributed Key Value Persistent Store as hashtable backend to store index.
 7369 *) LSHIndex is not string to text inverted index, but hashed string to text inverted index (something like a digital
 7370 *) Presently two types of hashes exist: primitive ordinal and MD5 hash
 7371 *) Only one hash table is implemented in Redis with multiple hash functions with random choice.
 7372 *) Presently 50 hash functions with 50 entries hash index has been implemented.
 7373
 7374 -----
 7375 403. (FEATURE-DONE) ThoughtNet Index implementation for NeuronRain AsFer Text and Crawled Web Documents Intrinsic Merit
 7376 -----
 7377 *) This commit implements an inverted index on top of ThoughtNet
 7378 *) ThoughtNet is a hypergraph stored in file and on Neo4j Graph Database
 7379 *) JSON loads ThoughtNet edges and hypergraph files and queries by classes returned by Recursive Gloss Overlap classi
 7380 *) Querying Neo4j is also better, but file representation of ThoughtNet is quite succinct and scalable because it jus
 7381 encodes each edge (= a web crawled **HTML** document)
 7382 *) file representation of ThoughtNet views the hypergraph as stack vertices interconnected by document id(s) similar
 7383 versioning system. Having similar view on a graph database doesn't look straightforward
 7384
 7385 -----
 7386 404. (FEATURE-DONE) Initial commits for Indexless Hyperball Recursive Web Crawler - 7 April 2017
 7387 -----
 7388 *) An indexless crawler which tries to find a url matching a query string in a recursive crawl creating a hyperball c
 7389 *) This is similar to Stanley Milgram, Kleinberg Lattice Small World Experiments and recent Hyperball algorithm for F
 7390 concluded that Facebook has 3.74 degrees of freedom.
 7391 *) Starts with a random url on world wide web.
 7392 *) Success probability depends on average number of hops over large number of queries.
 7393 *) This is a Randomized Monte Carlo Crawler and does a Depth First Search from an epicentre pivot url to start with
 7394 *) Hyperball References:
 7395 1) <http://webgraph.di.unimi.it/docs/it/unimi/dsi/webgraph/algo/HyperBall.html>
 7396 2) Facebook Hyperball - <https://arxiv.org/pdf/1308.2144.pdf>
 7397
 7398 -----
 7399 405. (THEORY) Indexless Web Search, World Wide Web Graph Property Testing, On-demand Indexing - related to 404 - 9 Ap
 7400 -----
 7401 Almost all known web search engines rely on a pre-built index created from already crawled WWW graph. Is a pre-built
 7402 web search? Can the small world property of world wide web graph (i.e property of graph such that easy short paths ex
 7403 of vertices as proved in Stanley Milgram experiment, Kleinberg Lattice), be applied to find a url matching a search c
 7404 vertex? Facebook graph has almost a billion user vertices and on an average any person is connected to any other with
 7405 Can this be generalized to world wide web? Traditional book index maps word queries to pages having the words. If ent
 7406 into a huge definition graph by Recursive Gloss Overlap graph, then instead of looking-up index, starting at a random
 7407 word should be easily reachable if graph has small world property. This realworld problem is already studied as Graph
 7408
 7409 References:
 7410 -----
 7411 405.1 Small World Property - [WattsStrogatz] - <http://www.nature.com/nature/journal/v393/n6684/full/393440a0.html>
 7412
 7413 -----
 7414 406. (FEATURE-DONE) Commit - NeuronRain AsFer CPython Extensions VIRG064 system call invocations - 20 April 2017
 7415 -----
 7416 *) VIRG064 system calls are invoked from Python code by CPython extensions.
 7417 *) Separate folder `cpython_extensions64/` has been created for 64bit VIRGO kernel
 7418 *) Requires Python 64-bit version
 7419 *) Logs for VIRG064 memory and filesystem systemcalls-to-drivers have been committed to testlogs
 7420 *) With this Complete Application Layer-SystemCalls-Drivers request routing for python applications deployed on VIRGC
 7421
 7422 -----
 7423 407. (FEATURE-DONE) Commits - NeuronRain AsFer Boost C++-Python - VIRG064 System calls + Drivers invocation - 26 April
 7424 -----
 7425 *) VIRG064 system calls are invoked from C++ by Boost::Python extensions
 7426 *) Kernel Logs for VIRGO KMemCache, Clone and FileSystem Calls Boost::python invocations have been committed to testl
 7427 *) Boost version used is 1.64.0
 7428 *) `setup.py` has been updated with `library_dirs` config variable

7429 *) virgofstest.txt for filesystem calls has been committed to testlogs/

7430

7431

7432 408. (FEATURE-DONE) Commits - 28 April 2017 - NeuronRain AsFer-Boost::Python-C++ - VIRG064 systemcalls and drivers in

7433 -----

7434 *) VIRG064 clone, kmemcache and filesystem system calls were invoked from Python-C++ boost extensions again and reprec

7435 without kernel panics.

7436 *) Logs, persisted disk file written by filesystem system calls and rebuilt boost-python C++ extensions have been com

7437 -----

7438 409. (THEORY) Condorcet Jury Theorem, Collaborative Filtering, Epistemological Democracy, Network Voting in WWW Link

7439 Majority Function and Correctness of Majority Vote Ranking - 16 May 2017, 23 May 2017

7440 -----

7441 Let v1, v2 be two vertices being good and bad choices respectively. In link graph all incoming edges to a vertex v1 a

7442 votes for that vertex. From Condorcet Jury Theorem if all incoming links occur with probability $p > 0.5$, then probabi

7443 -----

7444 More generically, vertex vx receives votes from vertices v1, v2, v3, ..., vyn with decision correctness probability p.

7445 -----

7446 Collaborative Filtering in Recommender Systems is the most generalized way of Majority Voting where a matrix of users

7447 -----

7448 References:

7449 -----

7450 409.1 Condorcet Jury Theorem and the truth on the web - <http://voxpublica.no/2017/03/condorcets-jury-theorem-and-the>

7451 409.2 Webometrics, Goodness of PageRank and Condorcet Jury Theorem - [MastertonOlssonAngere] - <https://link.springer>.

7452 409.3 Generalized Condorcet Jury Theorem, Free Speech, Correlated Voting (dependence of voters) - <https://www.jstor.c>

7453 -----

7454 410. (FEATURE-DONE) Commits - 17 May 2017 - NeuronRain AsFer-VIRG064 Boost-C++-Python invocations

7455 -----

7456 *) Boost Python C++ VIRG064 system calls were tested repeatedly in a loop

7457 *) All three system call subsystems - virgo_clone, virgo_kmemcache, virgo_filesystem - work well without any kernel p

7458 *) But a strange thing was observed: virgo filesystem system calls were not appending to disk file but when run as

7459 "strace -f python asferpythonextensions.py" disk file is written to (a coincidence or strace doing something special)

7460 -----

7461 411. (THEORY) Objective and Subjective Value Judgement, Text Ranking and Condorcet Jury Theorem - 29 May 2017 and 4 J

7462 - Related to 202, 385, 386 and all Recursive Lambda Function Growth and Recursive Gloss Overlap algorithms sections i

7463 -----

7464 Objective merit or Intrinsic merit of a document is the measure of meaningfulness or information contained in a docum

7465 -----

7466 Following are few real-world examples in addition to academic credentials example in 202:

7467 *) Soccer player, Cricket player or a Tennis player is measured intrinsically by number of goals scored, number of ru

7468 *) Merits of students are judged by examinations (question-answering) and not by majority voting by faculty. Thus que

7469 -----

7470 Present ranking algorithms are mostly majority voting (perception) oriented which is just half truth. Other half is t

7471 -----

7472 But how to measure "number of goals etc., " of a document vis-a-vis the rest? This is where Computational Linguistic T

7473 -----

7474 Condorcet Jury Theorem formalizes above intuition and bridges two worlds - objective reality and subjective perceptic

7475 -----

7476 Crucial Observation is: Merit creates Centrality (Social prestige) and not the opposite - Prestige can not create mer

7477 -----

7478 Alternatively, interview of document is simply the rank of the document in terms of intrinsic graph complexity merit

7479 *) Ranking text document by intrinsic graph complexity/entropy merit

7480 *) Relevance of the text to a query - graph edit distance

7481 -----

7482 Here again another question can be raised: Why is a graph representation of text an apt objective intrinsic merit mea

7483 -----

7484 There is special case of intrinsic merit: For example, reading a story creates a mental picture of it as a graph of e

7485 -----

7486 References:

7487 -----

7488 411.1 The Meaning of Meaning - <http://courses.media.mit.edu/2004spring/mas966/Ogden%20Richards%201923.pdf>

7489 411.2 WordNet and Word2Vec - <https://yaledatascience.github.io/2017/03/17/nnnlp.html> - In word2vec words from text ai

7490 411.3 Random Walks on WordNet - <http://anthology.aclweb.org/N/N15/N15-1165.pdf> - Recursive Lambda Function Growth alg

7491 -----

7492 412. (FEATURE-DONE) AngularJS - Tornado GUI-REST WebService - Commits - 1 June 2017

7493 -----

7494 NeuronRain AngularJS RESTful client for Tornado webserver and others

7495 -----

7496 *) AngularJS support has been added to NeuronRain GUI-WebServer with a new webserver_rest_ui/NeuronRain_AngularJS_RES

7497 and renders angularjs Model-View-Controller templates

7498 *) New AngularJS Model, View and Controller script-html templates have been added to angularjs directory

7499 *) LSHIndex.py has been updated to have commandline arguments for index queries

7500 *) Hyperball Crawler pivot epicentre url has been changed and an example query "Chennai" was found to be matching wit

7501 *) NeuronRain_REST_WebServer.py has been updated to print the logs for the script execution to browser console with s

7502 -----

7503 413. (THEORY) Graph Neural Networks, Tensor Neurons and Recursive Lambda Function Growth Intrinsic Merit - 4 June 201

```

7510 8 June 2017 - related to 411
7511 -----
7512 Definition Recursive Gloss Overlap Graph with word-word edges as Neuron Tensor Network relations having potentials w
7513   p(f(w1,w2)) = p(w1) * p(w2) for some operator *
7514
7515 Rather than mere summation of potentials of edges following minmax criterion extracts the most meaningful random walk
7516 *) Minimum Neuron Tensor Potential edge of each random walk is found - path minimum potential
7517 *) Maximum of all minimum path potentials extracts a random walk lambda composition tree which is the most probable i
7518
7519 Event Related Potentials (ERP) mentioned in 202 are unusual spikes in EEG of brain (N400 dataset) when unrelated word
7520
7521 Graph Neural Networks are recent models of neural network which generalize to a graph. In a Graph Neural Network, pot
7522
7523 Data on websites can be classified into 3 categories: 1) text 2) voice 3) images and videos. Intrinsic merit which is
7524
7525 Ranking text by Graph Tensor Neuron Network intrinsic merit potential can be done in multiple ways:
7526 - Rank Vertices and Edges by potential
7527 - Rank the random walk lambda function composition tree by potential
7528 - Rank by Körner Entropy of the Graph Tensor Neuron Network and other qualitative and quantitative graph complexity m
7529 and so on.
7530
7531 Example lambda composition tree on a random walk of recursive gloss overlap graph:
7532   f1 = requiredby(fuel, flight)
7533   f2 = has(flight, tyre)
7534   f3 = has(tyre, wheel)
7535   f4 = does(wheel, landing)
7536   f5 = requires(landing, gear)
7537   f1(fuel, f2(flight, f3(tyre, f4(wheel, f5(landing, gear)))))

7538
7539 Previous example random walk lambda composition tree has been constructed in 385 and 386. Potentials for Tensor Neurc
7540
7541 Difference in Graph Tensor Neuron Network mapping of a text is: Each lambda composition tree is evaluated as a Graph
7542
7543 Intuition for Graph Tensor Neuron Network is below:
7544 *) Random walk on recursive gloss overlap graph simulates randomness in cognitive cerebral text comprehension.
7545 *) Tensor Neuron relatedness potential between two word vertices in definition graph quantifies relevance and meaning
7546 *) Lambda composition tree-graph neural network for each random walk on definition graph simulates how meaning is rec
7547
7548 References:
7549 -----
7550 413.1 Graph Neural Networks - http://repository.hkbu.edu.hk/cgi/viewcontent.cgi?article=1000&context=vprd\_ja
7551
7552
7553 414. (FEATURE-DONE) Recursive Lambda Function Growth - Graph Tensor Neuron Network Implementation - Commits - 9 June
7554 -----
7555 (*) Recursive Lambda Function Growth implementation has been updated to compute Graph Tensor Neuron Network intrinsic
7556 (*) Each lambda function composition tree of a random walk on recursive gloss overlap graph is evaluated as a Graph N
7557 (*) Tensor neuron potential for relation edges in Graph Neural Network has been hardcoded at present and requires a c
7558 connective relations similar to EEG dataset for brain spikes in electric potentials.
7559
7560 -----
7561 415. (FEATURE-DONE) Graph Tensor Neuron Network - implementation update - Commits - 10 June 2017
7562 -----
7563 *) Changed the subtree graph tensor neuron network computation
7564
7565 *) Children of each subtree are the Tensor Neuron inputs to the subtree root
7566 Each subtree is evaluated as a graph neural network with weights for
7567 each neural input to the subtree root.
7568
7569 *) WordNet similarity is computed between each child and subtree root and is presently assumed as Tensor Neuron
7570 relation potential for the lack of better metric to measure word-word EEG potential.
7571 If a dataset for tensor neuron potential is available, it has to be looked-up and numeric
7572 potential has to be returned from here.
7573
7574 *) Finally a neuron activation function (simple 1-dimensional tensor) is computed and returned to the subtree root fo
7575
7576 *) logs for the this have been committed to testlogs. Presently graph tensor neuron network intrinsic merit is a very
7577 because of the decimal values of similarity and tensor neurons, but quite receptive to small changes.
7578
7579
7580 416. (FEATURE-DONE) Script for Querying Index (LSH and ThoughtNet) and Ranking the results with Recursive Lambda Func
7581 - Commits - 13 June 2017
7582 -----
7583 *) New python script QueryIndexAndRank.py has been committed for retrieving results from Index matching a query and r
7584 *) It queries both Locality Sensitive Hashing and ThoughtNet indices
7585 *) Functions of classes have been parametrized for invocation across modules
7586 *) Both LSH and ThoughtNet indices have been recreated
7587 *) Ranking is done by Recursive Lambda Function Growth algorithm which is a superset of Recursive Gloss Overlap
7588 *) This script was tested via NeuronRain Tornado RESTful GUI
7589
7590 -----

```

```

7591 417. (FEATURE-DONE) Graph Tensor Neuron Network Intrinsic Merit and QueryIndexAndRank update - Commits - 15 June 2017
7592 -----
7593 *) Graph Tensor Neuron Network Intrinsic Merit computation has been changed - Intrinsic merits of all random walks ar
7594 *) Some bugs fixed and debug prints have been changed
7595 *) logs have been committed to testlogs/
7596 -----
7597 418. (FEATURE-DONE) Hyperball crawler update - Commits - 19 June 2017
7598 -----
7599 Integrated Recursive Lambda Function Growth Intrinsic Merit Score(Graph Tensor Neuron Network and Korner Entropy) in
7600 -----
7601 419. (THEORY) Thought Experiment of Generic Intrinsic Merit and Condorcet Jury Theorem - 21 June 2017
7602 -----
7603 Intrinsic merit so far is restricted to text documents. Subjective ranking measures are like mirrors which reflect the
7604 candidate. Each vote in the majority voting is similar to an image of the voter projected on to the voter mirror. Some
7605 while others don't. Efficiency of a voter mirror is equivalent to decision correctness of a voter. Present web rankin
7606 (*) Peruse academic records and translate to score
7607 (*) Peruse work records and translate to score
7608 (*) Translate awards received to score
7609 (*) Translate brain imaging data to score (EEG and fMRI)
7610 (*) Translate IQ or EQ to score
7611 Above is not a formal algorithm but tries to intuit how it may look like. Human Resource Analytics are done as above
7612
7613 Objective Intrinsic Merit = Vote by an algorithm
7614 Subjective Ranking = Votes by people translated into rank by an algorithm (present ranking algorithms rely on incomin
7615 Thus Generic Intrinsic Merit removes human element completely while assessing merit (closer to AI). Goodness when it is
7616 (*) Question: Why should intrinsic merit be judged only in this way?
7617 (*) Answer: This is not the only possible objective intrinsic merit judgement. There could be other ways too. Disclaim
7618 (*) Question: Wouldn't cerebral representation vary from person to person and thus be subjective?
7619 (*) Answer: Yes, but there are standardized event related potential datasets gathered from multiple neuroscience exper
7620 (*) Question: Isn't perception based ranking enough? Why is such an intrusive objective merit required?
7621 (*) Answer: Yes and No. Perception majority voting based ranking is accurate only if all voters have decision correct
7622
7623 It was mentioned earlier that Fourier analysis of visuals and voice is the measure of intrinsic merit. Following defi
7624 Generic intrinsic merit of an entity - text, visual or voice - is the complexity of cerebral representation potential
7625
7626 References:
7627 -----
7628 419.1 Event Related Potentials for attractive facial recognition - https://labs.la.utexas.edu/langloislab/research/ev
7629 419.2 Event Related Potentials - http://cognitrn.psych.indiana.edu/busey/eegseminar/pdfs/Event-Related%2520Potentials
7630 -----
7631 420. (THEORY) Goodness of Link Graph Majority Voting and Complex Plane representation of merit - 22 June 2017 and 23
7632 -----
7633 Following is an example link graph in world wide web with weights for each edge:
7634     y1 - x1 : 0.25
7635     y1 - x2 : 0.25
7636     y1 - x3 : 0.25
7637     y1 - x4 : 0.25
7638 implying y1 votes to x1,x2,x3,x4 with weight 0.25 each.
7639
7640 Following is the corresponding initial decision correctness (goodness) graph with goodness for each edge:
7641     y1 - x1 : 0.25
7642     y1 - x2 : 0.25
7643     y1 - x3 : 0.375
7644     y1 - x4 : 0.125
7645 implying y1 votes to x1 with correctness 0.25, x2 with correctness 0.25, x3 with correctness 0.375 and x4 with correct
7646
7647 Markov iteration on the decision correctness graph (similar to random walk on link graph) tends to a stationary distr
7648     summation(weight(edge) * goodness(edge))
7649 For previous example cumulative goodness of voter y1 is:
7650     0.25*0.25 + 0.375*0.25 + 0.25*0.25 + 0.25*0.25 =
7651     1/32 + 3/32 + 2/32 + 2/32 = 0.25
7652
7653 If all votes are 100% correctly decided by y1, correctness graph has 1 for all edge weights. Thus cumulative goodness
7654     0.25 * 1 + 0.25 * 1 + 0.25 * 1 + 0.25 * 1 = 1 = 100%
7655 After markov iteration attains stationary distribution, cumulative goodness of all vertices also becomes stationary.
7656
7657 Following are the votes received by a vertex x1 from voters y1,y2,y3,y4 having respective cumulative goodness:
7658     y1 - x1: 0.75
7659     y2 - x1: 0.3 (voter with cumulative goodness < 0.5)
7660     y3 - x1: 0.8
7661     y4 - x1: 0.9
7662
7663 What is the probability in average case that atleast one voting vertex has cumulative goodness < 0.5? Link graph voti
7664
7665
7666
7667
7668
7669
7670
7671

```

```

7672 Pr[atleast one adjacent vertex y to a candidate vertex x has cumulative goodness < 0.5 after markov iteration] = 1 -
7673
7674 From Markov inequality tail bound, Pr[cumulative goodness > 0.5] <= mean/0.5
7675 Pr[cumulative goodness < 0.5] = 1 - Pr[goodness > 0.5] >= 1 - mean/0.5
7676 where mean is the average cumulative goodness of all vertices in link graph.
7677
7678 When mean is 0.5 (uniform distribution), Pr[cumulative goodness < 0.5] >= 1 - 0.5/0.5 = 0
7679 For any other values of mean < 0.5, Pr[atleast one adjacent vertex y to a candidate vertex x has cumulative goodness
7680
7681 In discrete random variable case, if goodness takes n discrete values between 0 and 1 then, mean = summation(x*p(x))
7682 n(n+1)/2*n*n = 0.5 + 0.5/n which tends to 0.5 when n tends to infinity.
7683 Thus mean cumulative goodness is 0.5 in uniform distribution.
7684
7685 Objective and Subjective rankings can be represented on a complex plane with following notation:
7686 (intrinsic merit=m) + i(perception=p) = m + ip
7687 where p is a function of m. Any text,visual or voice can be plotted on complex plane in previous notation. Ideally m
7688
7689 Riemann Hypothesis if true implies Re=0.5 for non trivial zeros of Riemann Zeta Function. If a set of complex number
7690
7691 Any k-coloring of a sequence of text and audio-visuals(AVs) denoted by integers is a classifier. 2-coloring or comple
7692 1111000011110000111000011100011111100000
7693
7694 ----- function f:
7695 ..... ----- complement g:
7696
7697 Vapnik-Chervonenkis Shattering or VC Shattering is defined as:
7698 Let H be a set of sets and C be a set. C is shattered by H if H intersection C = powerset of C = 2^C. Intuitively, H
7699
7700 2-coloring/complementation is a classifier on real line or integer sequences. 2 colors/binary encodings/complementati
7701
7702 References:
7703 -----
7704 420.1 Probability and Statistics with Reliability, Queuing and Computer Science Applications - Pages 223-225 - [Kishc
7705
7706 -----
7707 421. (THEORY) Human Resource Analytics, Interview Algorithm and Intrinsic Merit - related to 314, 360 and 366 - 26 Ju
7708 -----
7709 Stability of Interview TQBF circuit which is the theoretical formalism of Interview Algorithm Intrinsic Merit has bee
7710 (*) Construct a complete merit metric feature vector space for an individual based on past records( work and academic
7711 (*) Construct a contraction map(s) which contracts this merit vector space into a sample subspace. This contraction m
7712
7713 Real life interviews typically have following usecase (e.g IT industry) - a slightly modified version of previous TQE
7714 (*) suitability for a requirement
7715 (*) technical discussions (question-answering on programming/projects etc.,)
7716 (*) experience
7717
7718 Intrinsic Merit of Collection of Humans are measured in economics literature by many indices like GDP,Human Developme
7719 IPR(candidate)=geometric_mean(IPR(interview)*IPR(education)*IPR(experience))
7720
7721 From 359 and 365, NoiseSensitivity(InterviewTQBF) which is the dual of Stability is defined as:
7722 NoiseSensitivity(InterviewTQBF) = 0.5-0.5*Stability(InterviewTQBF) = 0.5-0.5*a^2*n^2/4
7723
7724 Error in interview is equal to NoiseSensitivity of interview TQBF. What is the probability of interview process faili
7725 Pr[Error in interview process > e ] <= mean/e where mean is the average error or NoiseSensitivity of interview
7726 Pr[Error in interview process > e ] <= NoiseSensitivity(InterviewTQBF)/e
7727
7728 While suitability can be easiliy quantified for error and interview TQBF having previous error bound, experience is a
7729 Experience = f(number of job/academic/private hops, intrinsic merit at each previous hop, experience per hop)
7730
7731 Interview algorithm being a TQBF satisfiability problem is PSPACE-complete (=IP=AP). There are existing question-answ
7732
7733 TQBF formulation of question-answering is far stringent than traditional interviews. Existential and Universal quanti
7734
7735 Intrinsic merit metric space of feature vector points can be construed as a Hypergraph with feature vector points as
7736
7737 Similar notion of transversal hypergraph can be applied to Recursive Gloss Overlap Definition Graph too (considering
7738
7739 Like usual text documents, candidate resumes can be represented as either a Recursive Gloss Overlap graph or a Thought
7740 *) Graph: Resume text is mapped to a graph by Recursive Gloss Overlap algorithm. Core number based classifier brings
7741 *) Hypergraph: Resumes are stored in ThoughtNet as Hypergraph index. Querying results in similar resumes. ThoughtNet
7742
7743 References:
7744 -----
7745 421.1 P,NP and examinations - https://terrytao.wordpress.com/2009/08/01/pnp-relativisation-and-multiple-choice-exams/
7746 421.2 Shrink Map and Contraction Map - [Topology - James Munkres] - pages 181-182
7747 421.3 Banach Fixed Point Theorem - https://en.wikipedia.org/wiki/Banach\_fixed-point\_theorem
7748 421.4 Davis-Putnam-Logemann-Loveland (DPLL) decision tree solver algorithm for QBF - http://personalpages.manchester.ac.uk/~elbassio/pub/COCOON05.pdf
7749 421.5 Parallel algorithm for Hypergraph Transversals - https://people.mpi-inf.mpg.de/~elbassio/pub/COCOON05.pdf
7750 421.6 Efficient algorithm for Hypergraph Transversals - http://jgaa.info/accepted/2005/KavvadiasStavropoulos2005.9.2.pdf
7751 421.7 Compendium of Intrinsic Performance Ratings in Chess - https://www.cse.buffalo.edu/~regan/papers/pdf/Reg12IPRs.pdf
7752 421.8 Human Development Index (New) - https://poseidon01.ssrn.com/delivery.php?ID=61510000800702408710908211206803106

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422. (FEATURE-DONE) Text Summarization from Recursive Gloss Overlap Graph Core - Commits - 28 June 2017

(*) Added a new function to create a summary from text - This function creates the core of a Recursive Gloss Overlap with certain core number and writes out a text sentence for each edge in core subgraph obtaining least common ancestor logs for this have been committed to python-src/testlogs

Summarization from k-core(s) of a Recursive Gloss Overlap graph captures the most crucial areas of the text because core vertices are the most prominent in the text.

423. (FEATURE-DONE) Text Summarization from Recursive Gloss Overlap Graph Core - Commits - 30 June 2017

(*) New clause added to classify the text and match the prominent core number word vertices in the text and only add (*) This is an alternative to k-core subgraph traversal and creating text programmatically. It is based on the heuristics to capture the essence/classes the text belongs to.

(*) Prominent core number classes are shaved off from the sorted core number list returned by RGO classifier and top 10 classes are selected.

424. (THEORY) Dense Subgraph Problem and Mining patterns in Graph Representation of Text - 2 July 2017

Recursive Gloss Overlap and Recursive Lambda Function Growth algorithms create graphs from text documents. Unsupervised prominent vertices of the definition graph and Text summarization at present depend on finding k-core subgraphs. In general problem to find Dense Subgraphs of a Graph where density of a subgraph S of a graph G is defined as:

$$d(S) = |\text{Edges of } S| / |\text{Vertices of } S|$$

There are polynomial time maxflow based algorithms and approximations to find dense subgraphs of a graph.

References:

424.1 Goldberg Algorithm, Charikar Algorithm and k-Cliques Densest Subgraph Algorithm for Dense Subgraph Discovery -

425. (THEORY) Pseudorandom non-majority choice and Bounded Electorate Majority Choice - 3 July 2017 - related to 53.7

Bounded Electorate Majority Choice:

Odd Electorate with 3 voters is the minimum possible majority voting setting which vouchsafes a clear winner. This is the case for all odd numbers of voters.

Pseudorandom Non-majority Choice:

Majority social choice has only one level of error probability i.e goodness for each voter while Non-majority pseudorandom choice has multiple levels of error probability.

Let number of voter decision functions with goodness $x_i = m(x_i)$. Total number of voters $N = m(x_1) + m(x_2) + m(x_3) + \dots + m(x_n)$. Effective goodness of a PRG choice is the mean:

$$1/N * \sum_{i=1}^N (x_i * m(x_i)) = (x_1 * m(x_1)) + (x_2 * m(x_2)) + (x_3 * m(x_3)) + \dots + (x_n * m(x_n)) / N$$

When all voter functions have goodness 1 then PRG choice has effective goodness 1.

Probability of choosing a voter of Goodness $x_i = m(x_i)/N$

Conditional goodness probability of a PRG chosen voter SAT =

$$\Pr[\text{choosing voter SAT of goodness } x_i] * \Pr[\text{goodness of SAT}] = [m(x_i)/N] * x_i$$

When $m(x_i) * x_i / N = 1$, Goodness of PRG choice is 1. This can happen only if $m(x_i) * x_i = N \Rightarrow m(x_i) = N$ and $x_i = 1$ i.e all voters have goodness 1.

When goodness is 1 for both LHS PRG choice and RHS Bounded Electorate Majority Choice, PRG choice is a BPP/BPNC/RNC/RF problem.

NP in P/poly also implies PH is in P/poly. It is not known if this implies PH-complete problems exist (because PH collapses to P/poly).

PH-completeness proof outline:

If NP is in BPP, NP is in P/poly because BPP is in P/poly.

$$\Rightarrow \text{If NP is in P/poly, PH is in } \Sigma(p,2) \text{ from Karp-Lipton-Sipser Collapse Theorem}$$

$$\Rightarrow \text{If NP is in P/poly, PH collapses to P/poly}$$

$$\Rightarrow \text{There are complete problems in each level } k \text{ of the Polynomial Hierarchy (correspond to a } k\text{-depth QBFSAT).}$$

$$\Rightarrow \text{There is a complete problem in } \Sigma(p,2) \text{ corresponding to 2-QBFSAT.}$$

$$\Rightarrow \text{All problems in } \Sigma(p,2) \text{ can be reduced to this } \Sigma(p,2)\text{-complete 2-QBFSAT problem.}$$

$$\Rightarrow \text{All problems in PH collapse to } \Sigma(p,2) \text{ if NP is in P/poly}$$

$$\Rightarrow \text{All problems in PH can be reduced to this } \Sigma(p,2)\text{-complete 2-QBFSAT problem.}$$

$$\Rightarrow \text{Sigma(p,2)-complete problem is thus a PH-Complete problem}$$

References:

425.1 Proof of Karp-Lipton-Sipser collapse theorem - PH in P/poly - <http://www.cse.iitm.ac.in/~jayalal/teaching/CS68/lectures/lec10.pdf>

426. (FEATURE-DONE) Updates to Text Summarization from Dense Subgraph of Recursive Gloss Overlap graph of a Text - Commits - 4 July 2017

(*) import matplotlib commented in RGO classifier

(*) New clause added to Text Summarization: This finds the common path between 2 word vertices synsets by inheriting existing WordNet code for shortest wordnet path distance and constructs sentences by a sliding window for each successive pair of intermediate vertices in this common path. This creates a deeper profound summary than least_common_hypernyms()

7834 (*) Logs for this have been committed to testlogs/.

7835

7836 It has to be noted that, dense subgraph traversal and writing unguided summary sans training data mimicks human recur

7837 comprehension and looks non-conventional for human reading. Presently only hypernym (IS A) relation is used for conne

7838 More comprehensive humane-looking summary can be created by Meronyms (HAS A) and Holonyms (IS PART OF) in WordNet API.

7839 presently there is no python API for ConceptNet5 and data has to be queried as RESTful JSON objects.

7840

7841 427. (FEATURE-DONE) Updates to Text Summarization - Commits - 5 July 2017

7842

7843 (*) Changed the class-sentence matching clause by increasing the percentile of prominent classes

7844 (*) Changed relevance_to_text() by comparing each sentence chosen by prominent class match to the sentences in text -

7845 Longest Common Subsequence matching difflib library function is invoked for this similarity. Sentences are chosen als

7846 (*) Percentage of summary to the size of the text has been printed as a ratio. Logs have been committed to testlogs/

7847

7848

7849 428. (FEATURE-DONE) Updates to Text Summarization - choosing sentences matching class labels - 6 July 2017

7850

7851 (*) Some experimentation on choosing relevant sentences to be added to summary was performed

7852 (*) relevance_to_text() invocation has been changed as per algorithm below:

7853 for each prominent dense subgraph k-core class label

7854 find the synset definition of class label

7855 for each sentence

7856 invoke relevance_to_text() similarity function between sentence and the class label definition

7857 and add to summary if the relevance ratio > 0.41 and if not already in summary

7858 (*) Ratio 0.41 was arrived at heuristically:

7859 - For relevance ratio 0.1, summary ratio was 0.65

7860 - For relevance ratio 0.2, summary ratio was 0.48

7861 - For relevance ratio 0.3, summary ratio was 0.35

7862 - For relevance ratio 0.4, summary ratio was 0.21

7863 - For relevance ratio 0.5, summary ratio was 0.02

7864 There is a drastic dip in size of summary if relevance threshold is increased beyond 0.4. Because of this 0.41 has be

7865 hardcoded.

7866 (*) Logs for this have been added to testlogs/

7867 (*) Summary generated is human readable - subset chosen from actual text.

7868

7869

7870 429. (FEATURE-DONE) ConceptNet 5.4 Python RESTful API implementation - lookup, search and association - 7 July 2017

7871

7872 (*) This commit implements the RESTful Python requests HTTP API for querying ConceptNet 5.4 dataset

7873 (*) Three functions for looking up a concept, searching a concept and finding similar associated concepts have been

7874 implemented with 3 endpoints (as per the documentation in <https://github.com/commonsense/conceptnet5/wiki/API/2349f2>)

7875 (*) ConceptNet is quite different from WordNet in representation as JSON dictionary as against graph in WordNet.

7876 (*) ConceptNet 5.4 endpoints have been invoked instead of 5.

7877 (*) If necessary ConceptNet can replace all WordNet invocations in a later point in time. But such a replacement is r

7878 probably require almost all Recursive Gloss Overlap related code to be rewritten from scratch. But that depends on hc

7879 weighs against WordNet in measuring semantic meaningfulness.

7880

7881

7882 430. (THEORY) Contradictions in bounds between finite and infinite electorate - 8,10,11,12,13 July 2017

7883

7884 Lowerbounds by equating the goodness of Non-majority and Majority social choice thus far mentioned in drafts in this

7885 (*) There are two possible paths to social choice - Non-majority and Majority

7886 (*) Each social choice belongs to a computational complexity class

7887 (*) Goodness of a social choice is the measure of error-free-ness of the choice made in either paths i.e deci

7888 (*) RHS Majority voting has been assumed to abide by Homeogeneous version of Condorcet Jury Theorem convergenc

7889 (*) Goodness of either choice majority or non-majority must be equal

7890 (*) Either LHS or RHS has to be a complete problem for a complexity class C.

7891 (*) Traditional literature on boolean majority functions and circuits assumes that input to majority is ready

7892 (*) Previous Oracle access based proofs have been intentionally circumvented by replacing Oracles with Boolean

7893 (*) Assuming all above, LHS is an algorithm for RHS complete problem (or viceversa) creating a lowerbound.

7894 (*) All bounds derived in this draft assuming above do not follow conventional lowerbound techniques e.g Circ

7895 (*) Most importantly drafts in this document are just analyses of various social choice functions, their comp

7896

7897

7898 Equality of Goodness of PRG choice and Majority voting for finite electorate of size 3:

7899

7900 Let x_1, x_2, x_3 be the goodness of 3 voter SATs. PRG choice randomly chooses one of the 3 voters while majority voting i

7901

7902 Goodness of PRG choice:

7903

7904 $= (x_1 * m(x_1) + x_2 * m(x_2) + x_3 * m(x_3)) / 3$

7905 When all 3 have equal goodness 1, effective goodness is:

7906 $= (1 * 1 + 1 * 1 + 1 * 1) / 3 = 1$

7907

7908 Goodness of Majority choice:

7909

7910 This is the bounded version of CJT binomial series summation. When $x_1=x_2=x_3=1$:

7911 $= (3C2(1)^2(0)^1 + 3C3(1)^3(0)^0) = (0 + 1) = 1$

7912

7913 Possible Lowerbounds described previously for Unbounded and Bounded electorate lead to contradictions as below:

7914 (*) In infinite voter case, homogeneous voter CJT circuit in BPP is derandomized to P if CJT converges => P=BPP.

```

7915 (*) In finite voter case, NP-complete RHS has BPP algorithm in LHS (NP in BPP) implying NP in P/poly and collapse of
7916
7917 Contradiction 1 :
7918 -----
7919 If BPP=P (unbounded CJT) and NP is in BPP (bounded) then NP is in P=BPP => P=NP. This conflicts with P != NP implied
7920      (*) the Majority Hardness Lemma (318),
7921      (*) Polytime learning of NP implying NP does not have polytime algorithms (368) and
7922      (*) HLMN PARITYSAT counterexample (53.15)
7923 but concurs with :
7924      (*) high percentage of random k-SATs satisfied in Approximate CNF SAT solver by least squares (376).
7925
7926 But can infinite voter CJT circuit be in BPP and thus in P/poly? Infinite voter CJT circuit is of polynomial size if
7927
7928 Contradiction 2 :
7929 -----
7930 If NP is in BPP and thus in P/poly (irrespective of BPP=P), similar conflicts arise. An assumption made in compositio
7931
7932 Reference 430.3 suggests there exists a random oracle A relative to which NC^A is in P^A. P having NP oracle access i
7933
7934 Replacing oracles with compositions and applying depth lowerbounds for Majority+VoterSAT circuit composition as below
7935      D(Maj + Voter) = CommunicationComplexity(R(Maj,Voter)) >= 5.3*logm + n - O(m*logm/n)
7936 does away with the hassles of relativization and directly gives the depth lowerbound of the majority voting circuit c
7937
7938 Example delta(p,2)-complete problem mentioned in 430.5:
7939 -----
7940 While number of queries to NP oracle <= k
7941 {
7942     (*) Query a 3SAT oracle for a satisfying assignment for a 3CNF Voter SAT
7943     (*) Store the queried satisfying assignment in a linked list in sorted order - this is linear per insertion i.
7944 }
7945 Output 1 if last element in the list ends with binary 1 digit.
7946
7947 This algorithm makes k queries to an NP oracle and has O(k^2) time complexity and thus in delta(p,2). Hardness follow
7948
7949 Mapping above delta(p,2) complete problem to proving completeness of NC1^NP majority voting is non-trivial. Majority
7950
7951 But this also implies that any Majority^A for a random oracle A is not complete if Majority is not complete for NC1.
7952
7953 Case 1 - s = 2^n:
7954 -----
7955 This makes the new majority circuit sans oracle to be of depth O(n*log2+c*log(n)) which is not polylog depth and poly
7956
7957 Case 2 - s = n^c:
7958 -----
7959 This new majority circuit has depth O(2*c*log(n)) and size O(n^2c) and is obviously in NC1 and computes majority. But
7960
7961
7962 References:
7963 -----
7964 430.1 Definition of Homogenous Voter - http://www.uni-saarland.de/fak1/fr12/csle/publications/2006-03\_condorcet.pdf
7965 430.2 Counting Classes and Fine Structure between NC and L - [Samir Datta , Meena Mahajan , B V Raghavendra Rao , Mic
7966 430.3 For a random oracle A, NC^A is strictly contained in P^A - https://complexityzoo.uwaterloo.ca/Complexity\_Zoo:N
7967 430.4 Delta(p,2) - P has NP oracle - https://complexityzoo.uwaterloo.ca/Complexity\_Zoo:D#delta2p
7968 430.5 Delta(p,2) complete problem - https://complexityzoo.uwaterloo.ca/Zooref#kre88 - [Krentel] - Given a Boolean for
7969 430.6 Spira theorem - any formula of leaf size s can be transformed into a formula of depth log(s) - https://www.math
7970 430.7 Size of a circuit composition - alternative form of KRW conjecture - http://www.math.ias.edu/~avi/PUBLICATIONS
7971 430.7 Size of a circuit composition - alternative form of KRW conjecture - http://www.math.ias.edu/~avi/PUBLICATIONS
7972 430.8 Log Depth circuits for Division and Related - [BeameCookHoover] - https://pdfs.semanticscholar.org/29c6/f0ade6c
7973 430.9 NC reducibility - reducing one NC instance to another - https://homes.cs.washington.edu/~ruzzo/papers/limits.pdf
7974 430.10 Catechism on open problems - Interview of Eric Allender - https://books.google.co.in/books?id=7z3VCgAAQBAJ&pg=PA11
7975 430.11 Parallel Computation and the NC hierarchy relativized - [Christopher Wilson] - https://link.springer.com/chapter/10.1007/978-3-319-15041-6\_11
7976
7977 -----
7978 431. (THEORY) Theoretical Formalism for an Electronic Voting Machine based on Locality Sensitive Hashing - 13 and 14
7979
7980 Locality Sensitive Hashing and their relevance to Multiway Contests have been described in 319. Voters voting for sam
7981
7982 Non-boolean social choice functions which a voter computes to obtain a candidate index have been described previously
7983      (*) receives voters in a streaming sequence,
7984      (*) each voter solves a non-boolean SAT (which could be in an arbitrary complexity class) having oracle acces
7985      (*) oracle returns a candidate index and counter is incremented
7986      (*) LSH based voting has a special step - it compares two voters for similarity i.e if their oracle queries r
7987      (*) Multipartisan SAT Oracle internally has to implement the following:
7988          - Iterate through all candidates
7989          - Find the maximum number of clauses that can be satisfied by each candidate and quantify it as score
7990          - Sort the scores for the candidates and return the topranked candidate.
7991      (*) Sort the LSH by length of buckets
7992      (*) MAXSAT has been used in lieu of Exact SAT for grading the candidates based on number of clauses satisfied.
7993      (*) Random k-CNF SAT Solver implemented in 276 approximates by solving system of equations by least squares.
7994      (*) Boolean Majority function is a special case of multipartisan voting: Restrict the number of candidates to
7995      (*) Voter SAT Oracles could be Constraint Satisfaction Problem(CSP) Solvers too which allow reals. This has be

```

7996
 7997 Circuit Value Problem finds if a circuit encoding evaluates to 1 or 0 for an input assignment. This is equivalent to
 7998 (*) Voter has a Constraint Satisfaction Problem (boolean or real)
 7999 (*) Candidate has an assignment to the variables of voter CSP (Prover)
 8000 (*) Voter verifies the assignment to CSP (Verifier)
 8001 This kind of Circuit Value Problem (CVP) formulation has been avoided throughout drafts in document for Majority Voti
 8002
 8003 References:
 8004 -----
 8005 431.1 Locality Sensitive Hashing - [Alex Andoni] - <http://web.mit.edu/andoni/www/LSH/index.html>
 8006 431.2 Lowerbounds for Locality Sensitive Hashing - [MotwaniAssafPanigrahi] - <http://theory.stanford.edu/~rinap/papers>
 8007 431.3 Optimal lowerbounds for Locality Sensitive Hashing - [ODonnell] - <https://www.cs.cmu.edu/~odonnell/papers/lsh.pdf>
 8008 431.4 Reflections on Trusting Trust - Trojan horses in code - program that prints itself - Quines - Godel,Escher,Bach
 8009 431.5 Problems with Electronic Voting Machines (e.g DRE machines), VVPAT and Trusting source code - [Bruce Schneier]
 8010 431.6 B-Cryptographic counters protocol augmented with Public Key Infrastructure for Incrementing Counters in Tabulat
 8011 431.7 PP is as hard as polynomial time hierarchy - [Toda] - <http://pubs.siam.org/doi/abs/10.1137/0220053?journalCode>
 8012
 8013 -----
 8014 432. (FEATURE-DONE and THEORY) Approximate CNF SAT Solver Update - percentage of clauses satisfied - 18 July 2017
 8015 -----
 8016 (*) This commit prints percentage of clauses satisfied for each random CNF 3SAT formula for both 0 and 1 evaluations
 8017 (*) logs for ~1000 iterations of random 3SAT have been committed to testlogs/
 8018 (*) Interestingly, even failing formula assignments by least squares satisfy more than 75% of clauses of the formula
 8019 (*) Percentage of formulas satisfied by least squares heuristic is ~70%
 8020 (*) This is probably a demonstration of complement form of Lovasz Local Lemma (LLL) for MAXSAT which is:
 8021 if events occur independently with a certain probability, there is a small non-zero probability that none of them wil
 8022 (*) Dual of LLL for this MAXSAT approximation is:
 8023 if each clauses are satisfied with a certain probability, there is a large probability that all of them are satisfied
 8024
 8025 References:
 8026 -----
 8027 432.1 Lovasz Local Lemma - https://en.wikipedia.org/wiki/Lovasz_local_lemma
 8028
 8029 -----
 8030 433. (THEORY) MAXSAT ranking of text documents, Approximate CNF SAT solver and Lovasz Local Lemma - related to 432 -
 8031 19 July 2017
 8032 -----
 8033 Considering a set of text documents, ranking function $r(X, A)$, is the subjective perception measure of a text X
 8034 with access to a perception oracle A :
 8035 $r(X, A)$ = subjective rank of X as perceived by an oracle A
 8036 In the context of web link graphs of **HTML** documents, every adjacent vertex of a node N is the perceiver of N and for
 8037 adjacent vertices A and B of N :
 8038 $r(X, A) = r(X, B)$ or $r(X, A) \neq r(X, B)$
 8039 Perception ranking of a node need not be decided just by adjacent vertices at the end of random walk markov iteration
 8040
 8041 Ranking of texts can be thought of as MAXSAT problem: Each reader of a text has a CNF (subjective) or all readers hav
 8042
 8043 Lovasz Local Lemma:
 8044 Let $a_1, a_2, a_3, \dots, a_n$ be set of events. If each event occurs with probability $< p$, and dependency digraph of these ever
 8045 $Pr[\bigwedge \neg a_i] > 0$, if $ep(d+1) < 1$ for $e=2.7128\dots$
 8046
 8047 CNF formula can be translated into a graph where each vertex corresponds to a clause and there is an edge between any
 8048
 8049 From LLL, If $p < 1/[e(d+1)]$ is the probability of an event (not satisfying a clause) :
 8050 Probability that clause is satisfied: $1-p > (1-1/[e(d+1)])$
 8051 Probability that all of the clauses are satisfied $> (1-1/[e(d+1)])^{(d+1)}$ (for $d+1$ clauses)
 8052 Probability that none of the clauses are satisfied $< 1-(1-1/[e(d+1)])^{(d+1)}$
 8053 In previous example $d+1 = 14$ and thus probability that none of the clauses are satisfied for any random CNF is:
 8054 $= 1-(1-1/[e(14)])^{(14)} < \sim 31.11\%$
 8055 and probability of all the clauses being satisfied for any random CNF is:
 8056 $(1-1/[e(14)])^{(14)} > \sim 68.89\%$
 8057
 8058 Experimental iterations of SAT solver converge as below (10000 CNFs):
 8059 Percentage of CNFs satisfied so far: 71.14
 8060 Average Percentage of Clauses per CNF satisfied: 97.505
 8061
 8062 This coincides with LLL lowerbounds above and far exceeds it because outdegree (common literals) is less and average
 8063
 8064 -----
 8065 434. (FEATURE-DONE) Approximate CNF SAT Solver update - Commits 1 - 19 July 2017
 8066 -----
 8067 (*) Average percentage of clauses satisfied per CNF is printed at the end of 10000 iterations
 8068 (*) AsFer Design Document updated for Lovasz Local Lemma analysis of least squares CNF SAT solver
 8069 (*) logs for least square assignment of 10000 random CNFs committed to testlogs/
 8070
 8071 -----
 8072 435. (FEATURE-DONE) Recursive Gloss Overlap Graph Classifier update - Commits 2 - 19 July 2017
 8073 -----
 8074 (*) printed Betweenness Centrality (BC) of the definition graph of a text
 8075 (*) BC of a node is the ratio of number of (s-t) shortest paths going through the node to all pairs shortest paths ar
 8076 thus measures how central a node is to the graph and thus is another basis for classifying a text apart from dense su

```

8077
8078 436. (FEATURE-DONE) Recursive Gloss Overlap graph classifier update - commits 1 - 20 July 2017
8079
8080 (*) Following centrality measures for the definition graph have been printed in sorted order and top vertices are com
8081     1) Betweenness Centrality
8082     2) Closeness Centrality
8083     3) Degree Centrality
8084     4) Eigenvector Centrality (PageRank)
8085     5) Core numbers Centrality (k-core dense subgraphs)
8086 (*) While first 3 centrality measures are reasonably equal in terms of ranking central vertices, PageRank centrality
8087     slightly different
8088 (*) But all 5 centrality measures reasonably capture the central purport of the text i.e the text on
8089     "Chennai Metropolitan Area Expansion to 8848 sqkm" is classified into "Area" which is the topranked central vertex
8090
8091
8092 437. (FEATURE-DONE) Approximate SAT Solver update - commits 2 - 20 July 2017
8093
8094 (*) Increased number of clauses and variables to 16 and iterated for ~3100 random CNF formulae.
8095 (*) Following are the MaxSAT percentages after ~3100 iterations:
8096 Percentage of CNFs satisfied so far: 69.1020276794
8097 Average Percentage of Clauses per CNF satisfied: 97.6122465401
8098 (*) Previous values are quite close to 14 clauses and variables iterations done previously.
8099
8100 Lovasz Local Lemma bound for 16 clauses all having common literals:
8101 = (1-1/[e(16)])^(16) > ~68.9233868%
8102 and average percentage of clauses satisfied after 3100 iterations far exceeds this bound at 97.61%
8103
8104 Commercially available SAT solvers (exact NP-complete decision tree evaluation based) usually scale to millions of cl
8105 this approximate polynomial time SAT solver does not have similar advantage, yet the huge percentage of clauses satis
8106
8107 Random number generator used in generating random CNF clauses is based on /dev/random and hardware generated entropy.
8108
8109 References:
8110 -----
8111 437.1 Linux Pseudorandom Generator - https://eprint.iacr.org/2012/251.pdf
8112
8113
8114 438. (FEATURE-DONE) Approximate SAT Solver update - 24 July 2017
8115
8116 (*) Increased number of variables and clauses to (20,20).
8117 (*) Changed SciPy lstsq() to NumPy lstsq() because NumPy has a faster lstsq() LAPACK implementation as against xGELSS
8118 (*) Logs for 100 random CNFs have been committed to testlogs/ and Percentage CNFs and Clauses satisfied are as below:
8119 Percentage of CNFs satisfied so far: 58.4158415842
8120 Average Percentage of Clauses per CNF satisfied: 97.1782178218
8121
8122
8123 439. (THEORY) Tight Hamiltonian Cycles and Independent Sets in ThoughtNet Hypergraph for Social Networks - related to
8124 421 and other sections on ThoughtNet - 25 July 2017 and 28 July 2017
8125
8126 Theoretical description of ThoughtNet Hypergraph as basis for evocative thought and text analysis is mentioned previc
8127
8128 Ranking people in social network can not be done in the same way as documents are ranked because of intrinsic merit a
8129
8130 Reference:
8131 -----
8132 439.1 Tight Hamiltonian Cycles in 3-uniform Hypergraphs - [Rodl-Rucinski-Szemerredi] theorem - https://web.cs.wpi.edu/
8133 439.2 Bianconi-Barabasi Social Network Model - https://en.wikipedia.org/wiki/Bianconi%20%26%20Barab%C3%A1si\_model -
8134 439.3 Experience versus Talent shapes the web - http://www.pnas.org/content/105/37/13724.full - following simplistic
8135     Let M be the natural ability/merit/fitness of a vertex and E be the experience.
8136
8137     Rate of change of experience of a social profile vertex is proportional to its intrinsic fitness and present
8138     Previous assumption is a heuristic on real-life experiences - intrinsic fitness is a constant while experienc
8139     Thus at any time point, experiential learning depends on how naturally meritorious a person is and how much p
8140     helpful in increasing experiential learning. (Might have some theoretical basis in Mistake bound in computati
8141     Following formalises how a boolean function is learnt incrementally from a dataset over time by making mistak
8142
8143     dE/dt = kME
8144     => dE = kME.dt
8145     => dE/E = kM.dt
8146     => log E = kMt + c
8147     => E = e^(kMt+c)
8148     => E = e^c * e^(kMt)
8149     => Experience is exponentially related to talent/merit/fitness
8150     => People with high natural ability amass same experience in less time compared to people with low merit
8151 At time t=0, E = e^c which is equal to natural ability/merit/fitness M of a social profile vertex in Bianconi-Barabas
8152 Therefore, E = M*e^(kMt). At t=0, experience equals merit and grows exponentially over time. But how to measure the f
8153 439.4 Bose-Einstein Condensation in Complex Networks - [Bianconi-Barabasi] - Physical Review Letters - http://barabas
8154 439.5 PAFit - Joint estimation of preferential attachment and node fitness in growing complex networks - [Thong Pham,
8155
8156
8157 440. (FEATURE-DONE) Scheduler Analytics for VIRGO Linux Kernel - Commits - 31 July 2017 and 1,3 August 2017

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8158 (*) As mentioned in NeuronRain FAQ at http://neuronrain-documentation.readthedocs.io/en/latest/, analytics driven lir
8159 is the ideal application of machine learning within kernel. There are two options to go about:
8160 (*) First is Application Layer Scheduling Analytics in which a python code for example, learns from linux kernel logs
8161 and /proc/<pid>/sched data of CFS and exports key-value pairs on how to prioritize processes' nice values in /etc/ker
8162 (*) Second is Kernel Layer Scheduling Analytics in which kernel has to make upcalls to userspace machine learning fur
8163 (*) Third option is to implement a separate kernel module with access to process waiting queue which loops in a kerne
8164
8165 First option is chosen for time being because:
8166 - it is top-down
8167 - it does not interfere in existing scheduler code flow much
8168 - minimal code change is required in kernel scheduler e.g as a KConfig build parameter and can be #ifdef-ed
8169 - key-value pair variable mechanism is quite flexible and broadcast kernelwide
8170 - any interested module in kernel can make use of them not just scheduler
8171 - it is asynchronous while kernel layer scheduling is synchronous (scheduler has to wait to know priority for
8172 - second and third options are circuitous solutions compared to first one.
8173 - Languages other than C are not preferable in kernel (http://harmful.cat-v.org/software/c++/linus)
8174 - Key-Value pair protocol between userspace and kernelspace effectively tames language barriers between user
8175 - Key-Value storage can also exist on a cloud too not necessarily in /etc/kernel_analytics.conf file thus tra
8176 - first option is more suited for realtime kernels
8177
8178 #####
8179 #Scheduler Analytics for Linux Kernel:
8180 #=====
8181 # Following DeepLearning models learn from process perf variables - CPU, Memory, Context switches, Number of Threads
8182 # for each process id retrieved by psutil process iterator - BackPropagation, RecurrentLSTM
8183 # RecurrentGRU and ConvolutionNetwork models learn software analytics neural networks from psutil process performance
8184 # Key value pairs learnt from these can be read by Linux Kernel Scheduler or anything else
8185 # and suitably acted upon for changing the process priorities dynamically. Any kernel module can make an upcall to th
8186 # executable and dump the key-value pairs in /etc/kernel_analytics.conf. Presently the implementation is quite primi
8187 # classifies the output layer of neural network into "Highest, Higher, High, Normal, Medium, Low, Lower and Lowest" p
8188 # in the format: <pid#deeplearningalgorithm>=<scheduled_priority_class>. Number of iterations has been set to 10 for
8189 #####
8190
8191 Following is a simulation of how the key-value pair for reprioritization from Scheduler Analytics could affect the kerr
8192     (*) Linux kernel scheduler has the notion of jiffies - HZ - set of clock ticks - for time slicing processes
8193     (*) Each priority class has a red-black binary search tree based queue - deletion is O(1) and insertion is O(l
8194     (*) On receipt of reprioritization analytics, kernel_analytics exports it kernelwide, scheduler reads this <pid>
8195     (*) Thus multiple red-black trees make a trade-off and rebalance periodically with no manual nice intervention
8196     (*) Every reprioritization is therefore O(logN).
8197     (*) In realtime bigdata processing of heavy load, priorities can change quite frequently. For m reprioritizati
8198
8199 References:
8200 -----
8201 440.1 Scheduler Activations - Effective Kernel Support for the user level management of parallelism - http://dl.acm.c
8202 440.2 Controlling Kernel Thread Scheduling From Userspace - http://citeseex.ist.psu.edu/viewdoc/download?doi=10.1.1.
8203
8204 -----
8205 441. (THEORY) Social Networks, Money Flow Markets, Pricing Equilibrium, Centrality, Intrinsic versus Perceptive Value
8206 and 11 August 2017
8207
8208 Flow of money in a network of buyers and sellers and pricing have been described in KingCobra design document - https
8209 In a flow market digraph, there is a directed edge from a vertex b to vertex s of weight p where b is a buyer, s is a
8210
8211 In money flow markets, each buyer i is allocated a good/service j of x(ij) units with utility u(ij) with price p(j).
8212
8213 Previous example is mooted to invoke the striking parallels between buyer versus seller price equilibrium and intrins
8214 Convex Program for Market Equilibrium is defined as below:
8215     Maximize u(ij)^e(i) where buyer i has money e(i) at disposal
8216 subject to:
8217     Total happiness of a customer = Sigma(u(ij)*x(ij)) where u(ij) is the utility buyer i gets from x(ij) units of
8218
8219 Following maps a Market to Merit equilibrium:
8220 Intrinsic merit of a (corresponds to Seller) vertex is defined by a feature vector of merit variables. Buyers are per
8221     Maximize u(ij)^e(i) where perceiver i has total perceived merit e(i) at disposal and u(ij) is the utility perc
8222 subject to:
8223     Total happiness of a perceiver = utility of i = Sigma(u(ij)*x(ij)) where u(ij) is the utility perceiver i gets
8224     and p(j) is the equilibrium perceived merit of a variable j
8225 Solving the previous convex program results in an optimal merit vector (set of p(j)'s) and weights of merit variables
8226
8227 This equilibrium is closely related to Nash Bargaining Problem which postulates existence of an agreement and disagre
8228
8229 References:
8230 -----
8231 441.1 Algorithmic Game Theory - Chapter 5 and Chapter 15 - Existence of Flow Markets Equilibrium and Nash Bargaining
8232 441.2 New Convex Program for Fisher Market Equilibria - Convex Program Duality, Fisher Markets, and Nash Social Welfa
8233 441.3 Triangle Inequality based Christofides 1/2-approximation Algorithm for Travelling Salesman Problem - Combinator
8234
8235
8236
8237 442. (FEATURE-DONE) Scheduler Analytics update - commits - 1 August 2017
8238

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8239 (*) Updated AsFer Design Document
8240 (*) Updated python_src/software_analytics/DeepLearning_SchedulerAnalytics.py to write in /etc/kernel_analytics.conf
8241 (*) logs committed to testlogs/
8242
8243
8244 443. (FEATURE-DONE) Graph Density (Regularity Lemma) and Bose-Einstein Fitness implementations - commits - 1 August 2
8245
8246 (*) New intrinsic merit measures based on graph density (regularity lemma) and Bose-Einstein intrinsic fitness have been invoked
8247
8248 (*) logs have been committed to testlogs/
8249
8250
8251 444. (THEORY) Mistake bound learning(MB), Experience and Intrinsic merit, Social Network Analytics - 2,3,11 August 26
8252
8253 Mistake bound learning, iteratively refines and converges from an initial hypothesis based on mistakes. PAC learning
8254
8255 Let M be the intrinsic merit (correctness) of a boolean function hypothesised in the form of conjunctions and disjunctions of experience(E) versus merit(M) as function of time(t):
8256
8257      $dE/dt = kME$ 
8258      $\Rightarrow dE = kME.dt$ 
8259      $\Rightarrow dE/E = kM.dt$ 
8260      $\Rightarrow \log E = kMt + c$ 
8261      $\Rightarrow E = e^{(kMt+c)}$ 
8262      $\Rightarrow E = M^*e^{(kMt)}$ 
8263
8264 If  $dE/dt$  is replaced by number of mistakes  $b1$  made and corrected per time unit in MB model and E is replaced by total
8265      $\Rightarrow E = M^*e^{(kMt)}$ 
8266      $\Rightarrow E = M^*e^{(kM^*b2/b1)}$ 
8267 Previous expression for experience depends both on intrinsic merit and mistakes made which is exactly required in human
8268
8269 Traditionally mistake bounds are used only in learning boolean functions. Generalizing it to any functions and humans
8270      $\Rightarrow E = M^*e^{(kM^*g(IQ,EQ)/f(IQ,EQ))}$ 
8271 If  $M=h(IQ)$ :
8272      $\Rightarrow E = h(IQ)*e^{(k*h(IQ)*g(IQ,EQ)/f(IQ,EQ))}$ 
8273
8274 It has to be mentioned here  $f$  is nothing but the first temporal derivative of  $g$  evaluated at time  $t$  i.e  $f = dg/dt$ .
8275      $\Rightarrow E = h(IQ)*e^{(k*h(IQ)*g(IQ,EQ)/g'(IQ,EQ))}$ 
8276
8277 Alternatively,  $f$  and  $g$  can be substituted directly if known and integrable:
8278      $g'(IQ,EQ) = k^*h(IQ)^*g(IQ,EQ)$ 
8279      $g''(IQ,EQ) = k^*h(IQ)^*g(IQ,EQ)$ 
8280      $\log g(IQ,EQ) = k^*M^*t + c$ 
8281      $g(IQ,EQ) = h(IQ)^*e^{(k^*h(IQ)^*t)}$ 
8282
8283 Curiously, function  $g$  which depends on  $EQ$  has no equivalent in RHS except time duration  $t$  and a constant  $k$ . This is probably
8284      $g(IQ1,EQ1) = h(IQ1)^*e^{(k^*h(IQ1)^*t1)}$ 
8285      $g(IQ2,EQ2) = h(IQ2)^*e^{(k^*h(IQ2)^*t2)}$ 
8286 Disclaimer: Previous model of merit based on IQ and EQ are purely presumptive and disputable because of lack of well-
8287
8288 This model is quite generic and should apply to any computable function including boolean learnt by mistake bounds. Future work
8289
8290 Mistakes in the social networks context are proportional to bounded rationality of the human social profile vertices
8291
8292 Thus following equivalence is conspicuous: Emotional Quotient (proportional to) Bounded Rationality (proportional to)
8293
8294 BackPropagation is a mistake bound deep-learning algorithm refining a perceptron by trial and error iterations. Previous work
8295 At time  $x$ , tree reaches level  $l(x)$ . Each node in the tree is a corrected mistake and each mistake corrected at level
8296
8297 Caveat is the previous recursive mistake correction tree is not traditional bottom-up evaluation circuit but is top-down
8298      $M = \langle m1, m2, m3, \dots, mn \rangle$  where each  $mi$  is the weight for a merit variable
8299 For example, Discrete Probability distribution for merit/least energy/fitness can be defined as:
8300      $Pr(M=mi) = mi/|M|$  where  $|M|$  is the L1 norm of  $M$ 
8301      $\Sigma(Pr(M=mi)) = (m1 + m2 + m3 + \dots + mn) / |M| = 1$ 
8302 Continuous Probability distribution is the polynomial passing through above merit weight points.
8303
8304 References:
8305 -----
8306 444.1 Mistake bound learning - https://www.cs.utexas.edu/~klivans/lec1.ps - In this teacher/learner model, learner iterates
8307 444.2 Learning quickly when irrelevant attributes abound - [Nick Littlestone] - http://citeseerx.ist.psu.edu/viewdoc
8308 444.3 Bounded Rationality and Satisficing - https://en.wikipedia.org/wiki/Bounded\_rationality
8309 444.4 Multiplex Networks with Intrinsic Fitness: Modeling the Merit-Fame Interplay via Latent Layers - [Babak Fotouhi]
8310 444.5 Relation between Intrinsic Merit of two vertices and probability of creating link between them - Page 27 - Equations
8311 444.6 First to Market is not Everything: an Analysis of Preferential Attachment with Fitness - [Christian Borgs, Jennifer Chayes]
8312      $\log(dv(t)) = cf * \log t$ 
8313      $f = \log(dv(t)) / c \log t$ 
8314     Since  $f=M$ ,  $E = M^*e^{(kMt)} = \log(dv(t)) * e^{(k \log(dv(t)) * t / c \log t)} / c \log t$ 
8315 444.7 Degree distribution and Intrinsic Fitness - https://www.cs.upc.edu/~CSN/slides/08network\_dynamics.pdf - "... Closely related to the concept of vertex intrinsic fitness"
8316 444.8 Ghadge et al Model of Intrinsic Fitness of a vertex - https://www.cs.umb.edu/~duc/publications/papers/ijpeds10.pdf
8317 444.9 Vertex Intrinsic Fitness in Social Networks - [Servedio, Caldarelli] - https://arxiv.org/pdf/cond-mat/0309659.pdf
8318 444.10 Bibliography listed in Social Networking: Mining, Visualization and Security - [Mrutyunjaya Panda, Satchidananda]
8319 444.11 Vertex Fitness defined in terms of Unfitness - Network growth models: A behavioural basis for attachment propensities

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8320 444.12 A 00-deformed Model of Growing Complex Networks with Fitness - [Massimo Stella , Markus Brede] - https://arxiv.org/abs/1207.1460
8321 444.13 Various Intrinsic Fitness Models - Barabasi-Albert, Barabasi-Bianconi, Ghadge Log Normal Fitness Attachment, C
8322
8323
8324 445. (FEATURE-DONE) Scheduler Analytics Update - Commits - 10 August 2017
8325
8326 (*) There is a problem in defining expected priorities in BackPropagation Neural Network output layer. This is necess
8327 weight update to happen iteratively and to quantify error between expected and actual neural network output
8328 (*) Output layer of BackPropagation is an indicator of process priority learnt by the perceptron.
8329 (*) Previously expected priorities were hardcoded. This has been changed as below:
8330     (*) Set of processes currently running are clustered and stored in an input JSON file
8331     (*) This JSON dictionary has key-value pairs mapping a process class to its apriori expected priority
8332     (*) Scheduler Analytics loads this JSON and looks up the expected priority for each process executable by its
8333     (*) Presently process class is just a substring of the executable name
8334     (*) BackPropagation does string match of this process class to executable name and finds the expected priorit
8335     (*) BackPropagation iteration updates the weights of all 3 layers
8336 (*) Defining apriori class of a process is subjective and instead of substring of executable, an independent clusteri
8337 suitable distance function can be used to write the JSON classification of processes. For example, unix process group
8338 processes.
8339 (*) Previous generation of JSON classes for processes and backpropagation weight update iteration is the first phase
8340 (*) In the second phase, weight-updated BackPropagation Neural Network takes as input runtime process statistics (CPU
8341 to predict the actual priority of a process belonging to the apriori class.
8342 (*) This is a depth 2 tree evaluation:
8343     Static - apriori expected class of a process and BackPropagation iteration
8344     Dynamic - fine grained priority of a process within the previous static class by evaluating the multilayer ne
8345
8346 Presently, input variables are per process CPU percentage, Memory percentage and ratio of involuntary context switche
8347
8348
8349 446.(FEATURE-DONE) Celestial Pattern Mining Update - specific to NeuronRain Research in SourceForge repositories - re
8350
8351 (*) Added a documentation text file asfer-docs/NeuronRain_Research_Celestial_Pattern_Mining.txt describing how astron
8352 mining is done and code involved therein.
8353
8354 (*) In python-src/autogen_classifier_dataset/MaitreyaToEncHoroClassified.py upgraded Maitreya's Dreams (http://www.safersolutions.com/~maitreya/)
8355 ephememeris text client version to 7.1.1
8356
8357 (*) Created separate string encoded astronomical data files for Earthquakes(USGS 100 year earthquake dataset) and
8358 Storms(NOAA 100 year HURDAT2 dataset) Datasets from python-src/autogen_classifier_dataset/MaitreyaToEncHoroClassified
8359 (zodiacal does not have ascendant, while ascrelative is rotated string relative to ascendant. Ascendant is defined as
8360 degree of the zodiac sign rising at the time of an event in eastern horizon)
8361
8362 (*) Executed python-src/SequenceMining.py on these 2 datasets. The results have been written to python-src/MinedClass
8363
8364 (*) python-src/autogen_classifier_dataset/asfer_dataset_segregator.sh has updated asfer relative location
8365
8366
8367 447. (FEATURE-DONE) Celestial Data Pattern Mining - Updates to autogen_classifier_dataset pre-processing and classifi
8368
8369 (*) An 8 year old lurking bug in cpp-src/NaiveBayesClassifier.cpp has been resolved. It was causing a null class to be
8370 bayesian argmax() computation.
8371 (*) Lot of new articles on earthquakes and hurricanes have been added as training dataset for NaiveBayesian Classifie
8372 have lot of research information on predicting hurricanes and earthquakes
8373 (*) python-src/autogen_classifier_dataset/AsferClassifierPreproc.py has been updated to include new articles in train
8374 (*) words.txt,word-frequency.txt,training-set.txt,topics.txt,test-set.txt have been re-created by executing python-sr
8375 (*) Datasets are classified into python-src/autogen_classifier_dataset/EventClassDataSet_Earthquakes.txt and python-s
8376
8377
8378 448. (FEATURE-DONE) Updated Ephemeris Search Script - Commits - 24 August 2017
8379
8380 Updated mined class association rule parsing in python-src/MaitreyaEncHoro_RuleSearch.py
8381
8382
8383 449. (FEATURE-DONE) Approximate CNFSAT Solver update - SciPy Sparse - 28 August 2017
8384
8385 (*) imported scipy.sparse.linalg least squares function lsqr().
8386 (*) Number of clauses and variables set to 18 each.
8387 (*) After 673 iterations of Random 3CNFs following satisfied clauses data were observed:
8388 Percentage of CNFs satisfied so far: 58.7537091988
8389 Average Percentage of Clauses per CNF satisfied: 97.0161556215
8390
8391 From LLL, If  $p < 1/[e(d+1)]$  is the probability of an event (not satisfying a clause) :
8392 Probability that clause is satisfied:  $1-p > (1-1/[e(d+1)])$ 
8393 Probability that all of the clauses are satisfied  $> (1-1/[e(d+1)])^{(d+1)}$  (for  $d+1$  clauses)
8394 Probability that some of the clauses are satisfied  $< 1-(1-1/[e(d+1)])^{(d+1)}$ 
8395
8396 If all clauses overlap:
8397 In previous example  $d+1 = 18$  and thus probability that all of the clauses are satisfied for any random CNF is :
8398  $(1-1/[e(18)])^{(18)} > \sim 68.96\%$ 
8399 and probability that some but not all of the clauses being satisfied for any random CNF is:
8400  $1-(1-1/[e(18)])^{(18)} < \sim 31.043\%$ 

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8401 If none of the clauses overlap:
8402 d=0 and probability that all the clauses are satisfied (1-1/e) > ~63.21%
8403 and probability that some but not all of the clauses being satisfied for any random CNF is < ~36.79%
8404
8405 -----
8406 450. (THEORY) Analysis of Error Upperbound for Approximate CNFSAT Solver based on Lovasz Local Lemma clause dependenc
8407 ,30 August 2017
8408 -----
8409 Probability of a clause being not satisfied from Lovasz Local Lemma:
8410     p < 1/(e(d+1))
8411 Probability of a clause being satisfied:
8412     1-p > 1 - 1/(e(d+1))
8413 Probability of all n clauses being satisfied (ExactSAT):
8414     (1-p)^n > [1 - 1/(e(d+1))]^n
8415 Probability of some or none of the clauses being satisfied:
8416     1-(1-p)^n < 1 - [1 - 1/(e(d+1))]^n
8417 If there are no overlaps, d=0:
8418     Probability of all n clauses being satisfied = (1-p)^n > [1 - 1/e]^n = [1 - 1/e]^n
8419     Probability of some or none of the clauses being satisfied = 1 - (1-p)^n < 1 - [1 - 1/e]^n
8420
8421 Probability of atleast k of n clauses being satisfied:
8422     Pr[#SATclauses >= k] = Pr[#SATclauses = k] + Pr[#SATclauses = k+1] + Pr[#SATclauses = k+2] + ... + Pr[#SATcl
8423
8424     = (1-p)^k + (1-p)^(k+1) + ... + (1-p)^n
8425
8426 if q = 1-p:
8427     = q^k + q^(k+1) + ... + q^n
8428     = q^k * (1 + q + q^2 + ... + q^(n-k))  [Geometric series]
8429     = q^k (1 - q^(n-k+1)) / (1-q)
8430 But from LLL, p < 1/e(d+1)
8431     q = 1 - p > (ed+e-1)/(ed+e)
8432
8433 Substituting for q:
8434     [(ed+e-1)/(ed+e)]^k [1 - [(ed+e-1)/(ed+e)]^(n-k+1)]
8435
8436     1 - [(ed+e-1)/(ed+e)]
8437
8438 #####
8439 #Probability of atleast k of n clauses being satisfied: #
8440 #     [ed+e-1]^k [(ed+e)^(n-k+1) - [ed+e-1]^(n-k+1)] #
8441 #     ----- #
8442 #     [(ed+e)^n] #
8443 #####
8444
8445 if k=n:
8446     (ed+e-1)^n / (ed+e)^n
8447
8448 If overlap of variables across the clauses is huge, ed+e-1 ~ ed+
8449 Maximum overlap d is (n-1) i.e a clause has common variables across all other clauses
8450
8451 When d is maximum:
8452 -----
8453 Lt (d -> n-1, n -> infinity) ((ed+e-1)/(ed+e))^n
8454     = [((e(n-1)+e-1)/(e(n-1) + e))^n
8455     = [(en-e+e-1)/(en-e+e)]^n
8456     = [(en-1)/(en)]^n
8457     = [(1-1/ne)]^n
8458     = [1 - 0.3678/n]^n
8459
8460 For infinite n:
8461     = e^(-0.3678)
8462 Pr[#SATclauses = n] = 69.22%
8463
8464 When overlap is absent at d=0:
8465 -----
8466 Pr[#SATclauses = n] = (e-1)^n/e^n = (0.6321)^n -> 0 for huge n
8467
8468 When d=1 (minimum overlap):
8469 -----
8470 Pr[#SATclauses = n] = [2e-1]^n / [2e]^n = [1-0.5/e]^n = (0.81606)^n -> 0 for huge n
8471
8472 => When the number of variables overlapping across clauses tends to a huge number almost equal to number of clauses,
8473 linear equations obtained by relaxing each of the clauses are solved by least squares and probability of all clauses
8474 to 69.22%. High overlap of variables across clauses is the most probable occurrence in real world SAT solvers. If th
8475     Expected value of d = 1/(n-1) * (n-1)n/2 = n/2
8476
8477 For mean overlap of n/2 variables across clauses:
8478 #####
8479 #Probability of atleast k of n clauses being satisfied: #
8480 #     [en/2+e-1]^k [(en/2+e)^n - [en/2+e-1]^n] #
8481 #     ----- #

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8482      [(en/2+e)^n] # 8483
8483      ##### 8484
8484      When k=n:
8485          [en/2+e-1]^n
8486          -----
8487          [en/2+e]^n
8488
8489          = [1 - 0.7357888/(n+1)]^n > [1 - 0.7357888/n]^n
8490          = Lt (n->infinity) [1 - 0.735758882/n]^n = e^-0.73578882
8491          => Pr[#SATclauses = n] > 47.91%
8492
8493      => When the number of variables overlapping across clauses are uniformly distributed, Probability of all clauses beir
8494      3CNF is lowerbounded as 47.91% when number of clauses tend to infinity.
8495      => Caveat: This is an average case analysis of overlaps and best case analysis for number of clauses satisfied. This
8496
8497      Correction to Geometric distribution LLL estimate:
8498
8499      Previous bound assumes  $\Pr[\#SATclauses \geq k]$  is geometric distribution. If  $k$  satisfying clauses are chosen from total
8500      8501      =>  $\Pr[\#SATclauses \geq k] = \sum_{l=k}^n (1-p)^l p^{n-l}$ 
8502      8503      If  $k=n/2$ , this summation is exactly same as Condorcet Jury Theorem where each clause in the 3CNF is a voter = probabi
8504      8505      When k=n:
8506
8507      Pr[#SATclauses = n] = (1-p)^n
8508      From LLL,  $e^{p(d+1)} > 1 \Rightarrow p > 1/e^{d+1}$ 
8509          1-p < 1 - 1/e^{d+1}
8510          1-p < 1 - 0.36788/(d+1)
8511          (1-p)^n < (1 - 0.36788/(d+1))^n
8512
8513      d=0, no overlaps:
8514
8515          Pr[#SATclauses=n] = (1-p)^n < (0.6321)^n which tends to 0 for huge number of clauses n.
8516
8517      d=n-1, maximum overlaps:
8518
8519          Pr[#SATclauses=n] = (1-p)^n < (1 - 0.36788/n)^n
8520          But Limit(n->infinity) (1 - 0.36788/n)^n = e^{(-0.36788)} = 0.692200241
8521          Pr[#SATclauses=n] < 69.22% for huge n.
8522
8523      d=n/2, expected overlaps in uniform distribution:
8524
8525          Pr[#SATclauses=n] = (1 - 1/(e(n/2+1)))^n = (1 - 0.735758882/(n+2))^n
8526          0.735758882/(n+2) < 0.735758882/n
8527          (1 - 0.735758882/(n+2))^n > (1 - 0.735758882/n)^n
8528          As n->infinity,  $(1 - 0.735758882/(n+2)) > e^{(-0.73578882)} \sim 47.91\%$ 
8529          => Pr[#SATclauses=n] > 47.91%
8530
8531      => 97-98% satisfied clauses found in few hundred iterations above for upto 20 clauses and 20 variables should tend as
8532          Pr[#SATclauses >= 0.98n] =  $\sum_{l=k}^n (1-p)^l p^{n-l}$ 
8533      This is tail bound for binomial distribution which is defined as:
8534           $\Pr[X \geq k] \leq e^{(-nD(k/n || p))}$ 
8535          where relative entropy  $D(k/n || p) = k/n \log(k/np) + (1-k/n) \log((1-k/n)/(1-p))$ 
8536          But  $k/n = 0.98n/n = 0.98$ 
8537           $D(k/n || p) = k/n \log(k/np) + (1-k/n) \log((1-k/n)/(1-p)) = 0.98 \log(0.98/p) + 0.02 \log(0.02/(1-p))$ 
8538          =>  $\Pr[X \geq 0.98n] \leq e^{(-n * (0.98 \log(0.98/p) + 0.02 \log(0.02/(1-p))))}$ 
8539          From LLL,  $p < 1/e^{d+1}$ . Substituting for p:
8540          =>  $\Pr[X \geq 0.98n] \leq e^{(-n * (0.98 \log(0.98e^{d+1}) + 0.02 \log(0.02(ed+e-1))))}$ 
8541          Lt(n->infinity)  $e^{(-n * (0.98 \log(0.98e^{d+1}) + 0.02 \log(0.02(ed+e-1))))} = 0$ 
8542
8543      Pr[#SATclauses <= n] <=  $e^{(-(np-n)^2/2pn)}$  by Chernoff bounds. From LLL,  $p < 1/e^{d+1}$ . For average number of overlaps
8544          Pr[#SATclauses <= n] <=  $e^{(-n/e)} \sim 69.22\%$  which coincides with maximum overlaps bound above.
8545
8546      Previous imply approximate CNF SAT solver by solving system of linear equations (= clauses relaxed to reals from bina
8547
8548      References:
8549
8550      450.1 Sum of Binomial Coefficients - http://web.maths.unsw.edu.au/~mikeh/webpapers/paper87.pdf - "... 000For years [t
8551      George E. Andrews in 1973] I had been trying to point out that the rather confused world of binomial coefficient summ
8552      450.2 Binomial Distribution Tail Bounds - https://en.wikipedia.org/wiki/Binomial\_distribution#Tail\_bounds
8553
8554
8555      451.(THEORY) Analysis of Error Upperbound for Approximate CNFSAT Solver based on Lovasz Local Lemma clause dependency
8556
8557      (*) Least Squares lsqr() function has been replaced by recent lsmr() least square function mentioned to be faster.
8558      (*) For 10 variables and 10 clauses for 54068 random 3CNF iterations following were the percentage of satisfied CNFs
8559      per CNF:
8560      Percentage of CNFs satisfied so far: 79.6722706172
8561      Average Percentage of Clauses per CNF satisfied: 97.6276609517
8562

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8563 (*) Again the percentage of clauses satisfied per random 3CNF converges to ~98% after ~54000 random 3CNFs.
8564 (*) The clauses are created by randomly choosing each literal and its negation independent of any other literal or cl
8565 (*) Repetitive convergence of number of clauses satisfied per CNF to 98% is mysterious in varied clause-variable comb
8566 (*) Previous error bound analysis does not assume least squares and is based only on LLL. But Least Squares is about
8567 (*) Motivation for least squares for boolean CNF is the relaxation achieved: An example assignment for a literal, 0.8
8568 (*) Convergence to 98% implies probability of average number of clauses satisfied per 3CNF > 0.98n must be almost 0.
8569 (*) Following Binomial Tail Bound:
8570 Pr[#SATclauses >= 0.98n] <= e^(-n*(0.98log(0.98e(d+1)) + 0.02log(0.02(ed+e)/(ed+e-1)))) is maximized when there are r
8571 Pr[#SATclauses >= 0.98n] <= e^(-n*(0.98log(0.98e) + 0.02log(0.02(e)/(e-1))))
8572 Pr[#SATclauses >= 0.98n] <= e^(-n*(0.41701 - 0.02999)
8573 Pr[#SATclauses >= 0.98n] <= e^(-n*0.38701) ~ 0 for large n.

8574
8575 -----
8576 452.(THEORY) PCP theorem, Hardness of Approximation, Least Squares SAT solver and Semidefinite Programming - related
8577 and 3 September 2017
8578 -----
8579 Probabilistically Checkable Proof theorem implies it is NP-hard to find satisfiable instances or 7/8+epsilon satisfia
8580
8581 References:
8582 -----
8583 452.1 PCP and hardness of approximation - algorithm satisfying 7/8+delta clauses - https://cs.stackexchange.com/questions/452.1
8584 452.2 SDP for MAX3SAT - http://www.isa.ewi.tudelft.nl/~heule/publications/sum\_of\_squares.pdf - Maximum number of clause
8585 452.3 Binary Solutions to System of Linear Equations - https://arxiv.org/pdf/1101.3056.pdf
8586 452.4 Karloff-Zwick 7/8 algorithm for MAX3SAT - http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.51.1351 - A ;
8587 452.5 Inapproximability results - [Johan Hastad] - https://www.nada.kth.se/~johanh/optimalinap.pdf - Assuming P != NP
8588 452.6 Gauss-Jordan Elimination For System of Linear Equations, Origin of Least Squares, Linear Programs for Inequalit
8589 452.7 Randomized Rounding for LP relaxation - https://en.wikipedia.org/wiki/Randomized\_rounding - Randomized Rounding
8590
8591 -----
8592 453.(THEORY) Approximate CNF 3SAT Solver - Least Squares Error Rounding Analysis - 9 September 2017,11 September 2017
8593 -----
8594 Notation:
8595 A' = Transpose of A
8596 A^-1 = Inverse of A
8597 E(A) = Expectation of A
8598 p(A) = probability of A
8599
8600 Rounding in least squares solution to system of equations per CNF 3SAT fails if and only if binary assignment obtaine
8601 A'Ax = A'b
8602 => x = (A'A)^-1*A'*b
8603 Number of satisfied clauses in least squares is = tr(A(A'A)^-1*A'*b) because Ax-b is minimized.
8604 Maximum value of tr(A(A'A)^-1*A'*b) is the maximum number of satisfied clauses
8605 if tr(A(A'A)^-1*A'*b) > 7/8*number_of_clauses, then P=NP by PCP theorem.
8606
8607 Each matrix A corresponding to a CNF is a random variable - A is a random matrix (not necessarily square).
8608 Expected value of A(A'A)^-1*A'*b where random matrix A belongs to some probability distribution = E(A(A'A)^-1*A'*b)
8609 E(A(A'A)^-1*A'*b) = b*E(A)*E((A'A)^-1)*E(A')
8610 E(A(A'A)^-1*A'*b) = b*E(A)*E((A'A)^-1)*E(A) because A and A' are bijections.
8611 E(A(A'A)^-1*A'*b) = b*E(A)*E(A'A)*E(A) because A'A and (A'A)^-1 are bijections.
8612 E(A(A'A)^-1*A'*b) = b*E(A)*E(A')*E(A')*E(A) by definition of product of expectations
8613 E(A(A'A)^-1*A'*b) = b*(E(A))^4
8614 E(A(A'A)^-1*A'*b) = b*(A*p(A))^4
8615 Each random matrix for a random 3CNF has nm entries where n is number of variables and m is number of clauses. Each c
8616
8617 Probability of choosing a variable or its negation = 1/(2n) for n variables + n negations.
8618 Probability of a random matrix A of mn entries = (1/(2n))^nm
8619 => E(A(A'A)^-1*A'*b) = b*(sigma(A(1/2n)^nm))^4 in uniform distribution.
8620 = b*(1/(2n))^nm * sigma(A))^4 which sums up all 2^nm possible boolean matrices.
8621 = b*(1/(2n))^nm * [ matrix of 2^(nm-1) for all entries ]^4
8622 = b * [ matrix of 2^(mn-1)/(2n)^nm for all entries ]^4
8623
8624 =====
8625 Tighter estimate for probability of a random 3CNF:
8626 =====
8627 Per clause 3 literals have to be chosen from 2n literals = 2nC3(1/2n)^3(1/2n)^(2n-3)
8628 For m clauses each being independent, Probability of a random 3CNF
8629 = (2nC3(1/2n)^3(1/2n)^(2n-3))^m
8630
8631 E(A(A'A)^-1*A'*b) = b * [ matrix of 2^(mn-1)/(2n)^nm for all entries ]^4 (1,m) * (m*n, n*m, m*n, n*m)
8632 = b * [ matrix of n^2*(2nm-2)/(2n)^2mn for all entries ]^2 (1,m) * (m*m, m*m)
8633 = b * [ matrix of m*n^2*2^(2nm-2)/(2n)^2mn for all entries ] (1,m) * (m*m)
8634 = [ matrix of m^2*n^2*2^(2nm-2)/(2n)^2mn for all entries ] (1,m)
8635 Trace of this expected matrix is the expected number of clauses that can be satisfied by least squares in uni
8636 = m^3*n^2*2^(2nm-2)/(2n)^2mn
8637 if number of clauses to be satisfied <= m, m^3*n^2*2^(2nm-2) <= m*(2n)^2mn
8638 => m^2*n^2*2^(2nm-2) <= (2n)^2mn
8639 which is obvious because (2n)^2mn grows faster.
8640 => m^2*n^2*2^2mn <= 4 * 2^2mn * n^2mn
8641 => m^2*n^2 <= 4 * n^2mn
8642 For all m clauses to be satisfied, this must be an equality:
8643 m^2 = 4 * n^2(m-1)

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8644 if m=n (number of clauses = number of variables), all clauses are satisfied if:
8645     n^2 = 4 * n^(n^2-1)
8646     n^2/4 = n^(n^2-1)
8647     => log (n^2/4) = (n^2-1) log(n)
8648     => log (n^2/4)/log(n) = (n^2-1)
8649     which is a contradiction because RHS grows faster.
8650 =====
8651 Alternatively, following simpler analysis leads to something more concrete:
8652     For minimum error x = (A'A)^-1*A'*b
8653     Ax=A(A'A)^-1*A'*b is maximum when A(A'A)^-1*A'*b = b
8654     => A(A'A)^-1*A' = I
8655 When A is square symmetric matrix (number of variables = number of clauses ) and A=A':
8656     => A(AA)^-1*A = I
8657     => Least squares perfectly solves system of equations for CNFSAT if matrix of clauses is symmetric and square
8658 Least squares thus solves a subset of NP-complete set of input 3CNFs i.e exactly solves a promise NP problem in deter
8659
8660 References:
8661 -----
8662 453.1 Advanced Engineering Mathematics - [Erwin Kreyszig - 8th Edition] - Page 357
8663 453.2 Linear Algebra - [Gilbert Strang] - http://math.mit.edu/~gs/linearalgebra/ila0403.pdf
8664 453.3 Least Squares Error - [Stephen Boyd] - https://see.stanford.edu/materials/lsoeldsee263/05-ls.pdf
8665
8666 -----
8667 454. (THEORY) Random Matrix Analysis of Least Squares Approximate CNFSAT solver - related to 453 - 15 September 2017
8668 -----
8669 From previous definition of expected value of random matrix equivalent to a random 3SAT:
8670     E(A(A'A)^-1*A'*b) = b*(E(A))^4
8671 Previous derivation of expected value of a random matrix is further simplified by a different definition of expectati
8672     E(A) = [ matrix of E(x(i,j)) ] i.e each entry of the matrix is evaluated independently.
8673 Let the probability of each entry x(i,j) of the random matrix = p. Each entry is a literal or its negation and can ta
8674     E(x(i,j)) = p
8675     => E(A) = [ matrix of p for all entries ]
8676     => b * (E(A))^4 = b*[ matrix of np^2 for all entries ]^2
8677     = b*[ matrix of m*n^2*p^4 for all entries ]
8678     = [ matrix of m^2*n^2*p^4 for all entries ]
8679     E(A(A'A)^-1*A'*b) = [ matrix of m^2*n^2*p^4 for all entries ]
8680     Trace(E(A(A'A)^-1*A'*b)) = m^3*n^2*p^4 which has maximum value equal to number of clauses m
8681     => m^3*n^2*p^4 <= m
8682     => m^2*n^2*p^4 <= 1
8683     => p^4 <= 1/(mn)^2
8684     => p^2 <= 1/(mn)
8685     => p <= 1/sqrt(mn)
8686 This retrieves the probability distribution of the random 3SAT instances.
8687 If all clauses have to be satisfied (ExactSAT), p = 1/sqrt(mn).
8688 In previous example iterations of the solver, number of clauses = number of variables i.e p = 1/n.
8689 This differs from the uniform probability assumption 1/(2n) per literal in earlier derivations including the negation
8690 The promise subset of NP solved exactly by least squares is defined by the set of all random 3CNFs created with each
8691 literal occurring with probability 1/n.
8692
8693 References:
8694 -----
8695 454.1 Random matrices - http://www.utstat.toronto.edu/~brunner/oldclass/431s09/readings/RandomMatrices.pdf
8696
8697 -----
8698 455. (FEATURE and THEORY) Commits - Approximate SAT solver - 15 September 2017
8699 -----
8700 (*) Some debug statements have been included to print average probability of each literal's occurrence in random 3CNF
8701 (*) SATsolver has been re-executed with 20 clauses and 20 variables and probability of occurrence of each literal has
8702 (*) This was necessitated to ascertain the pseudorandomness of the clauses and CNFs created.
8703 (*) Average probability of a literal is less than previous estimate of 1/n = 1/20 = 0.05 for 100% satisfied clauses b
8704 (*) logs committed to testlogs/
8705
8706 -----
8707 456. (THEORY) Eigenvalues of Random Matrices, Riemann Zeta Function, MAXSAT ranking of merit, Promise problems and Sc
8708 -----
8709 The set of random 3CNFs created by the solver is just a subset of all possible 3CNFs because all least squares API in
8710 Earlier the problem of intrinsically ranking texts etc., based on merit has been reduced to a MAXSAT problem where ea
8711 Random Matrix representation of random 3SAT instances throws up an unusual window into the realm of Riemann Zeta Func
8712
8713 References:
8714 -----
8715 456.1 Promise Problems - http://www.cs.tau.ac.il/~amnon/Classes/2017-BPP/Lectures/Lecture11.pdf
8716 456.2 Survey of Promise Problems - [Oded Goldreich] - http://www.wisdom.weizmann.ac.il/~oded/PSX/prpr-r.pdf - there e
8717 456.3 Gaussian Unitary Ensemble - Random Matrices - http://empslocal.ex.ac.uk/people/staff/mrwatkin//zeta/random.htm
8718
8719 -----
8720 457. (THEORY and FEATURE) CNF3SAT Approximate Solver Update - All possible variable-clause combinations - Commits - 1
8721 -----
8722 (*) Solve_SAT2() function has been changed to take both number of variables and clauses as parameters
8723
8724

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```

8725  (*) Bug in EquationsB creation has been fixed so that length of b equals number of clauses. This was causing dimensions
8726  in LSMR and LSQR
8727  (*) Logs for 18*16 clauses-variables random 3CNFs have been committed to testlogs/. MaxSAT percentage is ~96% after 1
8728  . Per literal probability is too less than 1/sqrt(mn) obtained from random matrix analysis and therefore converges much
8729  faster
8730  -----
8731  (*) Bugs fixed in prob_dist()
8732  (*) restored lsmr()
8733  (*) logs for some other clause-variable combinations have been committed to testlogs/. Observed per literal probability
8734  matrix probability of 1/sqrt(mn)

8735  -----
8736 458. (THEORY and FEATURE) Inapproximability and Random Matrix Analysis of Least Square Approximate SAT solver - Commi
8737  -----
8738 Previous Random Matrix Analysis shows expected number of satisfied clauses =  $m^3 \cdot n^2 \cdot p^4$  where there are m clauses, n
8739  probability of choosing a positive or negative literal. For 21 variables and 20 clauses, following are the results af
8740  -----
8741  -----
8742 Iteration : 29
8743  -----
8744 solve_SAT2(): Verifying satisfying assignment computed .....
8745  -----
8746 a: [[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8747 [0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0]
8748 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
8749 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8750 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
8751 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8752 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8753 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8754 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8755 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8756 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8757 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
8758 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8759 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8760 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
8761 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8762 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8763 [0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8764 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
8765 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
8766 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
8767 b.shape: (20, 21)
8768 b.shape: (20,)
8769 solve_SAT2(): lstsq(): x: (array([- 5.00000000e-01,  0.00000000e+00,  0.00000000e+00,
8770   1.00000000e+00,  3.89920951e-13,  1.00000000e+00,
8771   1.00000000e+00,  5.00000000e-01,  7.50000000e-01,
8772   1.00000000e+00,  5.00000000e-01,  7.50000000e-01,
8773   1.24863661e-13,  0.00000000e+00,  0.00000000e+00,
8774   0.00000000e+00,  5.00000000e-01,  5.00000000e-01,
8775   1.00000000e+00,  5.00000000e-01,  0.00000000e+00]), 2, 12, 1.870828693386971, 5.2032984761241552e-12, 4.89
8776 Random 3CNF: (!x11 + !x3 + !x13) * (!x2 + x12 + x11) * (x20 + x11 + !x10) * (!x1 + !x2 + x11) * (x5 + !x10 + x19) * (
8777 Assignment computed from least squares: [1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0]
8778 CNF Formula: [['!x11', '!x3', '!x13'], ['!x2', 'x12', 'x11'], ['x20', 'x11', '!x10'], ['!x1', '!x2', 'x11'], ['x5', 'x11']]
8779 Number of clauses satisfied: 20.0
8780 Number of clauses : 20
8781 Assignment satisfied: 1
8782 Percentage of clauses satisfied: 100.0
8783 Percentage of CNFs satisfied so far: 46.6666666667
8784 Average Percentage of Clauses per CNF satisfied: 96.0
8785 y= 46
8786 sumfreq= 896
8787 y= 43
8788 sumfreq= 896
8789 y= 36
8790 sumfreq= 896
8791 y= 46
8792 sumfreq= 896
8793 y= 41
8794 sumfreq= 896
8795 y= 42
8796 sumfreq= 896
8797 y= 48
8798 sumfreq= 896
8799 y= 37
8800 sumfreq= 896
8801 y= 48
8802 sumfreq= 896
8803 y= 39
8804 sumfreq= 896
8805 y= 46

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```

8806 sumfreq= 896
8807 y= 42
8808 sumfreq= 896
8809 y= 42
8810 sumfreq= 896
8811 y= 50
8812 sumfreq= 896
8813 y= 39
8814 sumfreq= 896
8815 y= 33
8816 sumfreq= 896
8817 y= 41
8818 sumfreq= 896
8819 y= 42
8820 sumfreq= 896
8821 y= 44
8822 sumfreq= 896
8823 y= 43
8824 sumfreq= 896
8825 y= 48
8826 sumfreq= 896
8827 y= 40
8828 sumfreq= 904
8829 y= 43
8830 sumfreq= 904
8831 y= 51
8832 sumfreq= 904
8833 y= 36
8834 sumfreq= 904
8835 y= 38
8836 sumfreq= 904
8837 y= 46
8838 sumfreq= 904
8839 y= 44
8840 sumfreq= 904
8841 y= 36
8842 sumfreq= 904
8843 y= 41
8844 sumfreq= 904
8845 y= 45
8846 sumfreq= 904
8847 y= 46
8848 sumfreq= 904
8849 y= 34
8850 sumfreq= 904
8851 y= 46
8852 sumfreq= 904
8853 y= 46
8854 sumfreq= 904
8855 y= 36
8856 sumfreq= 904
8857 y= 42
8858 sumfreq= 904
8859 y= 44
8860 sumfreq= 904
8861 y= 47
8862 sumfreq= 904
8863 y= 51
8864 sumfreq= 904
8865 y= 54
8866 sumfreq= 904
8867 y= 38
8868 sumfreq= 904
8869 Probability of Variables chosen in CNFs so far: [0.05133928571428571, 0.04799107142857143, 0.04017857142857143, 0.051
8870 Probability of Negations chosen in CNFs so far: [0.04424778761061947, 0.04756637168141593, 0.05641592920353982, 0.039
8871 Average probability of a variable or negation: 0.047619047619
8872 Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0487950036474
8873 -----
8874 From PCP theorem and [Hastad] inapproximability result based on it, if  $m^3 \cdot n^2 \cdot p^4 > 7/8 \cdot m$  then P=NP.
8875  $\Rightarrow m^2 \cdot n^2 \cdot p^4 > 7/8$ 
8876  $\Rightarrow p^4 > 7/(8m^2n^2)$ 
8877  $\Rightarrow$  if  $p > 0.96716821/\sqrt{mn}$  then P=NP.
8878
8879 In previous iteration, y and sumfreq print the frequencies of literals chosen so far at random (which are almost ever
8880 Expected number of clauses satisfied =  $(20)^3 \cdot (21)^2 \cdot (0.047619)^4 = 18.1405$  clauses or 90.7025%
8881 implying the MaxSAT for 21 variables and 20 clauses converges to 90.7025% asymptotically ad infinitum.
8882
8883 The inequality  $m^3 \cdot n^2 \cdot p^4 > 7/8 \cdot m$  relates hardness and randomness because probability distribution for p is directly
8884
8885 For a binary valued random variable X, bias(X) is defined as  $\Pr(X=0) - \Pr(X=1) \leq \epsilon$ . Epsilon biased pseudorandom
8886

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8968 Thus there are two possible probability distributions for choosing a random 3SAT: (1/[mn])^1.5m required by Random Ma
8969
8970
8971 If m=n(number of clauses and number of variables are equal):
8972 -----
8973 (1/[nn])^1.5n = (1/n)^3n and thus both RMLSQR and Uniform distributions are same implying similar pseudorandomness in
8974
8975 If m !=n e.g m >> n (this is most prevalent setting where number of clauses are huge and variables are relatively les
8976 -----
8977 (1/[mn])^1.5m < (1/n)^3m
8978 (1/m)^1.5m * (1/n)^1.5m < (1/n)^1.5m * (1/n)^1.5m
8979 (1/m)^1.5m < (1/n)^1.5m
8980 1/m < 1/n
8981 => m > n
8982
8983 When number of clauses m differs from number of variables n, RMLSQR and Uniform distributions are dissimilar implying
8984 randomness-es: PRG1 for RMLSQR and PRG2(or perfect randomness) for Uniform. Distinguisher for these two random genera
8985
8986
8987 461. (THEORY and FEATURE) Random Matrix Rounding for Least Squares Approximate CNFSAT Solver - various clause-variabl
8988
8989 Following are some random 3SAT iteration MAXSAT percentage numbers for multiple combinations of number of variables &
8990 this could be error in estimating linux PRNG probability distribution. Deficiencies of Linux PRNGs - especially randc
8991
8992 #####
8993 17 variables, 18 clauses - 1066 random 3SATs:
8994 #####
8995
8996 Iteration : 1066
8997
8998 solve_SAT2(): Verifying satisfying assignment computed .....
8999
9000 a: [[0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9001 [0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9002 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
9003 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0]
9004 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9005 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9006 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9007 [0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9008 [0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0]
9009 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9010 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
9011 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9012 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
9013 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0]
9014 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9015 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
9016 [0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
9017 [0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0]]
9018 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
9019 a.shape: (18, 17)
9020 b.shape: (18,)
9021 solve_SAT2(): lstsq(): x: (array([ 0.0000000e+00, 1.0000000e+00, 8.0000000e-01,
9022 1.0000000e+00, 2.0000000e-01, 1.0000000e+00,
9023 1.0000000e+00, 6.66666667e-01, 6.0000000e-01,
9024 0.0000000e+00, 0.0000000e+00, -6.66666667e-01,
9025 6.0000000e-01, 1.89190298e-14, 6.66666667e-01,
9026 4.0000000e-01, 0.0000000e+00]), 2, 11, 1.653279569018299, 9.190906242470613e-13, 4.690415759823429, 4.19
9027 Random 3CNF: (x3 + !x11 + !x16) * (!x16 + x3 + x5) * (x6 + !x9 + !x4) * (x15 + !x10 + x8) * (!x14 + x2 + !x8) * (!x11
9028 Assignment computed from least squares: [0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0]
9029 CNF Formula: [['x3', '!x11', '!x16'], ['!x16', 'x3', 'x5'], ['x6', '!x9', '!x4'], ['x15', '!x10', 'x8'], ['!x14', 'x2
9030 Number of clauses satisfied: 18.0
9031 Number of clauses : 18
9032 Assignment satisfied: 1
9033 Percentage of clauses satisfied: 100.0
9034 Percentage of CNFs satisfied so far: 61.0121836926
9035 Average Percentage of Clauses per CNF satisfied: 97.3341664063
9036 y= 1675
9037 sumfreq= 28722
9038 y= 1683
9039 sumfreq= 28722
9040 y= 1716
9041 sumfreq= 28722
9042 y= 1750
9043 sumfreq= 28722
9044 y= 1699
9045 sumfreq= 28722
9046 y= 1690
9047 sumfreq= 28722
9048 y= 1697

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9049 sumfreq= 28722
9050 y= 1662
9051 sumfreq= 28722
9052 y= 1732
9053 sumfreq= 28722
9054 y= 1740
9055 sumfreq= 28722
9056 y= 1687
9057 sumfreq= 28722
9058 y= 1669
9059 sumfreq= 28722
9060 y= 1677
9061 sumfreq= 28722
9062 y= 1662
9063 sumfreq= 28722
9064 y= 1664
9065 sumfreq= 28722
9066 y= 1660
9067 sumfreq= 28722
9068 y= 1659
9069 sumfreq= 28722
9070 y= 1716
9071 sumfreq= 28896
9072 y= 1782
9073 sumfreq= 28896
9074 y= 1660
9075 sumfreq= 28896
9076 y= 1714
9077 sumfreq= 28896
9078 y= 1704
9079 sumfreq= 28896
9080 y= 1716
9081 sumfreq= 28896
9082 y= 1721
9083 sumfreq= 28896
9084 y= 1688
9085 sumfreq= 28896
9086 y= 1679
9087 sumfreq= 28896
9088 y= 1653
9089 sumfreq= 28896
9090 y= 1662
9091 sumfreq= 28896
9092 y= 1686
9093 sumfreq= 28896
9094 y= 1702
9095 sumfreq= 28896
9096 y= 1673
9097 sumfreq= 28896
9098 y= 1735
9099 sumfreq= 28896
9100 y= 1678
9101 sumfreq= 28896
9102 y= 1727
9103 sumfreq= 28896
9104 Probability of Variables chosen in CNFs so far: [0.058317665900703294, 0.05859619803634844, 0.05974514309588469, 0.06
9105 Probability of Negations chosen in CNFs so far: [0.059385382059800665, 0.061669435215946845, 0.05744739756367663, 0.06
9106 Average probability of a variable or negation: 0.0588235294118
9107 Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0571661950475
9108 #####
9109 18 variables, 19 clauses - 137 random 3SATs:
9110 #####
9111 -----
9112 Iteration : 137
9113 -----
9114 solve_SAT(): Verifying satisfying assignment computed .....
9115 -----
9116 a: [[1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9117 [0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
9118 [0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0]
9119 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9120 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9121 [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0]
9122 [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
9123 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9124 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1]
9125 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9126 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9127 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9128 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
9129 [0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0]

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9130]
9131 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9132 [0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0]
9133 [0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0]
9134 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9135 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
9136 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1]]
9137 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
9138 a.shape: (19, 18)
9139 b.shape: (19,)
9140 solve_SAT(): lstsq(): x: (array([-6.66666667e-01, 1.00000000e+00, -1.1111111e-01,
9141 3.3333333e-01, 0.00000000e+00, 1.00000000e+00,
9142 4.4444445e-01, 1.66666667e+00, 8.93039852e-11,
9143 0.00000000e+00, 0.00000000e+00, 6.66666667e-01,
9144 -6.66666666e-01, 0.00000000e+00, -5.55555556e-01,
9145 6.66666667e-01, -8.43769499e-15, 1.00000000e+00]), 2, 13, 2.0816659994661344, 5.027196399901854e-09, 5.29
9146 Random 3CNF: (x4 + x1 + !x7) * (!x3 + x6 + x9) * (x3 + x12 + x7) * (!x13 + !x4 + !x10) * (x12 + x16 + !x6) * (x12 + !x15)
9147 Assignment computed from least squares: [1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1]
9148 CNF Formula: [['x4', 'x1', '!x7'], ['!x3', 'x6', 'x9'], ['x3', 'x12', 'x7'], ['!x13', '!x4', '!x10'], ['x12', 'x16'],
9149 Number of clauses satisfied: 19.0
9150 Number of clauses : 19
9151 Assignment satisfied: 1
9152 Percentage of clauses satisfied: 100.0
9153 Percentage of CNFs satisfied so far: 52.8985507246
9154 Average Percentage of Clauses per CNF satisfied: 96.7581998474
9155 y= 220
9156 sumfreq= 3952
9157 y= 243
9158 sumfreq= 3952
9159 y= 252
9160 sumfreq= 3952
9161 y= 230
9162 sumfreq= 3952
9163 y= 195
9164 sumfreq= 3952
9165 y= 203
9166 sumfreq= 3952
9167 y= 231
9168 sumfreq= 3952
9169 y= 225
9170 sumfreq= 3952
9171 y= 224
9172 sumfreq= 3952
9173 y= 228
9174 sumfreq= 3952
9175 y= 221
9176 sumfreq= 3952
9177 y= 224
9178 sumfreq= 3952
9179 y= 205
9180 sumfreq= 3952
9181 y= 216
9182 sumfreq= 3952
9183 y= 199
9184 sumfreq= 3952
9185 y= 206
9186 sumfreq= 3952
9187 y= 203
9188 sumfreq= 3952
9189 y= 227
9190 sumfreq= 3952
9191 y= 207
9192 sumfreq= 3914
9193 y= 218
9194 sumfreq= 3914
9195 y= 214
9196 sumfreq= 3914
9197 y= 220
9198 sumfreq= 3914
9199 y= 223
9200 sumfreq= 3914
9201 y= 204
9202 sumfreq= 3914
9203 y= 220
9204 sumfreq= 3914
9205 y= 233
9206 sumfreq= 3914
9207 y= 203
9208 sumfreq= 3914
9209 y= 210
9210 sumfreq= 3914
9211 y= 234

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9211 sumfreq= 3914
9212 y= 208
9213 sumfreq= 3914
9214 y= 239
9215 sumfreq= 3914
9216 y= 180
9217 sumfreq= 3914
9218 y= 205
9219 sumfreq= 3914
9220 y= 232
9221 sumfreq= 3914
9222 y= 259
9223 sumfreq= 3914
9224 y= 205
9225 sumfreq= 3914
9226 Probability of Variables chosen in CNFs so far: [0.05566801619433198, 0.06148785425101214, 0.06376518218623482, 0.058
9227 Probability of Negations chosen in CNFs so far: [0.05288707204905468, 0.05569749616760347, 0.054675523760858456, 0.05
9228 Average probability of a variable or negation: 0.0555555555556
9229 Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0540738070436
9230
9231 #####
9232 19 variables, 18 clauses - 34 random 3SATs
9233 #####
9234 -----
9235 Iteration : 34
9236 -----
9237 solve_SAT2(): Verifying satisfying assignment computed .....
9238 -----
9239 a: [[0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0]
9240 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9241 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0]
9242 [0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0]
9243 [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
9244 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
9245 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9246 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0]
9247 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9248 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9249 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
9250 [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1]
9251 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9252 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9253 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9254 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9255 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9256 [0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
9257 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
9258 a.shape: (18, 19)
9259 b.shape: (18,)
9260 solve_SAT2(): lstsq(): x: (array([ 1.00000000e+00, 1.00000000e+00, 1.00000000e+00,
9261 1.00000000e+00, 1.00000000e+00, 1.00000000e+00,
9262 -3.65332764e-15, 0.00000000e+00, 0.00000000e+00,
9263 9.05525654e-15, 1.00000000e+00, 1.00000000e+00,
9264 0.00000000e+00, 9.05525654e-15, 0.00000000e+00,
9265 -1.00000000e+00, 1.00000000e+00, 3.34888367e-14,
9266 -3.65332764e-15]), 2, 12, 1.414213562373095, 2.09387713811129e-13, 4.795831523312719, 3.8125525032467102, 3.
9267 Random 3CNF: (x4 + x14 + x10) * (!x2 + !x11 + x5) * (x16 + x2 + x17) * (!x8 + x11 + x7) * (!x5 + x11 + !x14) * (x4 +
9268 Assignment computed from least squares: [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0]
9269 CNF Formula: [['x4', 'x14', 'x10'], ['!x2', '!x11', 'x5'], ['x16', 'x2', 'x17'], ['!x8', 'x11', 'x7'], ['!x5', 'x11',
9270 Number of clauses satisfied: 18.0
9271 Number of clauses : 18
9272 Assignment satisfied: 1
9273 Percentage of clauses satisfied: 100.0
9274 Percentage of CNFs satisfied so far: 80.0
9275 Average Percentage of Clauses per CNF satisfied: 98.7301587302
9276 y= 52
9277 sumfreq= 942
9278 y= 39
9279 sumfreq= 942
9280 y= 46
9281 sumfreq= 942
9282 y= 50
9283 sumfreq= 942
9284 y= 53
9285 sumfreq= 942
9286 y= 43
9287 sumfreq= 942
9288 y= 47
9289 sumfreq= 942
9290 y= 51
9291 sumfreq= 942

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9292 y= 57
9293 sumfreq= 942
9294 y= 48
9295 sumfreq= 942
9296 y= 54
9297 sumfreq= 942
9298 y= 49
9299 sumfreq= 942
9300 y= 46
9301 sumfreq= 942
9302 y= 61
9303 sumfreq= 942
9304 y= 54
9305 sumfreq= 942
9306 y= 44
9307 sumfreq= 942
9308 y= 48
9309 sumfreq= 942
9310 y= 49
9311 sumfreq= 942
9312 y= 51
9313 sumfreq= 942
9314 y= 44
9315 sumfreq= 948
9316 y= 42
9317 sumfreq= 948
9318 y= 43
9319 sumfreq= 948
9320 y= 43
9321 sumfreq= 948
9322 y= 61
9323 sumfreq= 948
9324 y= 60
9325 sumfreq= 948
9326 y= 49
9327 sumfreq= 948
9328 y= 60
9329 sumfreq= 948
9330 y= 43
9331 sumfreq= 948
9332 y= 57
9333 sumfreq= 948
9334 y= 47
9335 sumfreq= 948
9336 y= 60
9337 sumfreq= 948
9338 y= 49
9339 sumfreq= 948
9340 y= 41
9341 sumfreq= 948
9342 y= 60
9343 sumfreq= 948
9344 y= 46
9345 sumfreq= 948
9346 y= 53
9347 sumfreq= 948
9348 y= 41
9349 sumfreq= 948
9350 y= 49
9351 sumfreq= 948
9352 Probability of Variables chosen in CNFs so far: [0.055201698513800426, 0.041401273885350316, 0.04883227176220807, 0.0
9353 Probability of Negations chosen in CNFs so far: [0.046413502109704644, 0.04430379746835443, 0.04535864978902954, 0.04
9354 Observed Average probability of a variable or negation: 0.0526315789474
9355 Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0540738070436
9356 Percentage of Clauses satisfied - Observed Average Probability substituted in Random Matrix Analysis of Least Squared
9357
9358 #####
9359 16 variables, 15 clauses - 60 random 3SATs
9360 #####
9361 -----
9362 Iteration : 60
9363 -----
9364 solve_SAT2(): Verifying satisfying assignment computed .....
9365 -----
9366 a: [[0 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
9367 [0 0 1 0 0 0 0 0 0 1 0 0 0 0 0]
9368 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9369 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
9370 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
9371 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
9372 [0 1 0 0 0 0 0 1 0 0 0 0 0 0 0]

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9373 [0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0]
9374 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9375 [0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
9376 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9377 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9378 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9379 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9380 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
9381 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
9382 a.shape: (15, 16)
9383 b.shape: (15,)
9384 solve_SAT2(): lstsq(): x: (array([
  0.00000000e+00, 4.00000000e-01, 1.00000000e+00,
  1.00000000e+00, -2.00000000e-01, 1.00000000e+00,
  0.00000000e+00, 6.00000000e-01, 6.00000000e-01,
  8.00000000e-01, -2.28234722e-16, 0.00000000e+00,
  5.00000000e-01, 5.00000000e-01, 1.00000000e+00,
  0.00000000e+00]), 2, 9, 1.5491933384829675, 1.3065051242742054e-12, 4.242640687119285, 2.7186789946524619, 2
9385 Random 3CNF: (!x8 + x10 + !x11) * (x11 + x3 + !x8) * (!x10 + !x16 + !x1) * (!x8 + x6 + !x4) * (x9 + !x1 + !x10) * (!x
9386 Assignment computed from least squares: [0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0]
9387 CNF Formula: [['!x8', 'x10', '!x11'], ['x11', 'x3', '!x8'], ['!x10', '!x16', '!x1'], ['!x8', 'x6', '!x4'], ['x9', '!x
9388 Number of clauses satisfied: 15.0
9389 Number of clauses : 15
9390 Assignment satisfied: 1
9391 Percentage of clauses satisfied: 100.0
9392 Percentage of CNFs satisfied so far: 65.5737704918
9393 Average Percentage of Clauses per CNF satisfied: 97.1584699454
9394 y= 75
9395 sumfreq= 1376
9396 y= 95
9397 sumfreq= 1376
9398 y= 77
9399 sumfreq= 1376
9400 y= 79
9401 sumfreq= 1376
9402 y= 96
9403 sumfreq= 1376
9404 y= 89
9405 sumfreq= 1376
9406 y= 79
9407 sumfreq= 1376
9408 y= 94
9409 sumfreq= 1376
9410 y= 86
9411 sumfreq= 1376
9412 y= 93
9413 sumfreq= 1376
9414 y= 101
9415 sumfreq= 1376
9416 y= 91
9417 sumfreq= 1376
9418 y= 92
9419 sumfreq= 1376
9420 y= 80
9421 sumfreq= 1376
9422 y= 77
9423 sumfreq= 1376
9424 y= 72
9425 sumfreq= 1376
9426 y= 93
9427 sumfreq= 1369
9428 y= 82
9429 sumfreq= 1369
9430 y= 82
9431 sumfreq= 1369
9432 y= 84
9433 sumfreq= 1369
9434 y= 85
9435 sumfreq= 1369
9436 y= 84
9437 sumfreq= 1369
9438 y= 87
9439 sumfreq= 1369
9440 y= 87
9441 sumfreq= 1369
9442 y= 84
9443 sumfreq= 1369
9444 y= 71
9445 sumfreq= 1369
9446 y= 80
9447 sumfreq= 1369
9448 y= 74
9449 sumfreq= 1369
9450 y= 90
9451 sumfreq= 1369
9452 y= 91
9453

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```

9454    sumfreq= 1369
9455    y= 100
9456    sumfreq= 1369
9457    y= 100
9458    sumfreq= 1369
9459    y= 88
9460    sumfreq= 1369
9461    y= 78
9462    sumfreq= 1369
9463    Probability of Variables chosen in CNFs so far: [0.05450581395348837, 0.0690406976744186, 0.0559593023255814, 0.05741
9464    Probability of Negations chosen in CNFs so far: [0.0679327976625274, 0.05989773557341125, 0.05989773557341125, 0.0620
9465    Observed Average probability of a variable or negation: 0.0625
9466    Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0645497224368
9467    Percentage of Clauses satisfied - Observed Average Probability substituted in Random Matrix Analysis of Least Squared
9468
9469 #####21 variables, 18 clauses - 6 random 3SATs#####
9470 #####21 variables, 18 clauses - 6 random 3SATs#####
9471 -----
9472 Iteration : 6
9473 -----
9474 solve_SAT2(): Verifying satisfying assignment computed ....
9475 -----
9476 a: [[0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0]
9477 [0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
9478 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0]
9479 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9480 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9481 [1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1]
9482 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9483 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
9484 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
9485 [0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9486 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0]
9487 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9488 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
9489 [0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0]
9490 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9491 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9492 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9493 [0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
9494 [0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
9495 b: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
9496 a.shape: (18, 21)
9497 b.shape: (18,)
9498 solve_SAT2(): lstsq(): x: (array([- 5.00000000e-01, 1.00000000e+00, 0.00000000e+00,
9499 5.00000000e-01, 1.00000000e+00, 0.00000000e+00,
9500 -2.63027447e-16, 1.00000000e+00, -3.67351548e-14,
9501 0.00000000e+00, 8.39171896e-12, 9.28077060e-17,
9502 0.00000000e+00, -3.67351548e-14, 0.00000000e+00,
9503 2.65906351e-12, 1.00000000e+00, -2.52681990e-14,
9504 5.00000000e-01, 1.00000000e+00, 5.00000000e-01]), 2, 12, 1.7320508075688767, 6.3185165416969518e-11, 4.8
9505 Random 3CNF: (x11 + x8 + x16) * (!x12 + x11 + x5) * (!x4 + x17 + x18) * (x5 + !x18 + !x8) * (!x8 + x21 + x1) * (!x9 +
9506 Assignment computed from least squares: [1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1]
9507 CNF Formula: [['x11', 'x8', 'x16'], ['!x12', 'x11', 'x5'], ['!x4', 'x17', 'x18'], ['x5', '!x18', '!x8'], ['!x8', 'x21
9508 Number of clauses satisfied: 18.0
9509 Number of clauses : 18
9510 Assignment satisfied: 1
9511 Percentage of clauses satisfied: 100.0
9512 Percentage of CNFs satisfied so far: 71.4285714286
9513 Average Percentage of Clauses per CNF satisfied: 97.619047619
9514 y= 10
9515 sumfreq= 184
9516 y= 9
9517 sumfreq= 184
9518 y= 5
9519 sumfreq= 184
9520 y= 7
9521 sumfreq= 184
9522 y= 10
9523 sumfreq= 184
9524 y= 2
9525 sumfreq= 184
9526 y= 11
9527 sumfreq= 184
9528 y= 5
9529 sumfreq= 184
9530 y= 8
9531 sumfreq= 184
9532 y= 13
9533 sumfreq= 184
9534 y= 14

```

```

9535 sumfreq= 184
9536 y= 9
9537 sumfreq= 184
9538 y= 8
9539 sumfreq= 184
9540 y= 10
9541 sumfreq= 184
9542 y= 4
9543 sumfreq= 184
9544 y= 9
9545 sumfreq= 184
9546 y= 11
9547 sumfreq= 184
9548 y= 9
9549 sumfreq= 184
9550 y= 10
9551 sumfreq= 184
9552 y= 9
9553 sumfreq= 184
9554 y= 11
9555 sumfreq= 184
9556 y= 8
9557 sumfreq= 194
9558 y= 14
9559 sumfreq= 194
9560 y= 9
9561 sumfreq= 194
9562 y= 11
9563 sumfreq= 194
9564 y= 7
9565 sumfreq= 194
9566 y= 10
9567 sumfreq= 194
9568 y= 11
9569 sumfreq= 194
9570 y= 11
9571 sumfreq= 194
9572 y= 11
9573 sumfreq= 194
9574 y= 11
9575 sumfreq= 194
9576 y= 6
9577 sumfreq= 194
9578 y= 11
9579 sumfreq= 194
9580 y= 4
9581 sumfreq= 194
9582 y= 6
9583 sumfreq= 194
9584 y= 11
9585 sumfreq= 194
9586 y= 3
9587 sumfreq= 194
9588 y= 8
9589 sumfreq= 194
9590 y= 14
9591 sumfreq= 194
9592 y= 4
9593 sumfreq= 194
9594 y= 13
9595 sumfreq= 194
9596 y= 11
9597 sumfreq= 194
9598 Probability of Variables chosen in CNFs so far: [0.05434782608695652, 0.04891304347826087, 0.02717391304347826, 0.038
9599 Probability of Negations chosen in CNFs so far: [0.041237113402061855, 0.07216494845360824, 0.04639175257731959, 0.05
9600 Observed Average probability of a variable or negation: 0.047619047619
9601 Probability per literal from Random Matrix Analysis of Least Squared (1/sqrt(mn)): 0.0514344499874
9602 Percentage of Clauses satisfied - Observed Average Probability substituted in Random Matrix Analysis of Least Squared
9603 -----
9604 462. (THEORY) Space-Filling, Random Close Packing, Bin Packing and Voter Decision Functions - 27 October 2017 - relat
9605 -----
9606 Parallel PRG and Cellular Automaton Algorithms for randomly filling a space with objects and their relevance to Linea
9608
9609 Reference:
9610 -----
9611 462.1 Random Close Packings of Spheres in a Container - Space-filling and Structural Topology - http://www.math.corne
9612 -----
9613 463. (THEORY) Reduction from Random Close Packing to CNFSAT - related to 462 - 30 October 2017
9614 -----
9615

```

9616 Each random close pack after a random shuffle shifts the centre of an n-sphere. Set of all possible centroids of an n-sphere
 9617 (C11 V C12 V C13 ...) /\ (C21 V C22 V C23 ...) /\ (C31 V C32 V C33 ...) /\ ...
 9618 Each Cik is assumed to be boolean variable which is 1 if n-sphere si is located in centroid Cik in random close pack
 9619
 9620 Randomized Algorithm (Parallel PRG or Cellular Automaton) for this space filling random close pack finds a satisfying
 9621 pack is the limit on density = Total Volume of Spheres (or) Total number of satisfied clauses / Volume of Container.
 9622
 9623 Filling the space within the container by n-spheres in parallel monte carlo random choice of centroids, simulates mar
 9624
 9625 -----
 9626 464. (FEATURE-DONE) Ephemeris Search Script Update - Celestial Pattern Mining - 31 October 2017
 9627 -----
 9628 Updated Ephemeris Search for Sequence Mined Celestial Configurations - `toString()` function has been changed to concat
 9629 for vacant zodiac signs while creating encoded celestial chart.
 9630
 9631 -----
 9632 465. (FEATURE-DONE) Ephemeris Search - Sequence Mining of Tropical Monsoon for mid-November 2017 - 1 November 2017
 9633 -----
 9634 (#) *Apriori GSP SequenceMining on autogen_classifier_dataset historic Storms data has been executed*
 9635 (#) *asfer.anchors.seqmining has been updated from autogen_classifier_dataset*
 9636 (#) *MinedClassAssociationRules.txt has been rewritten containing almost 2500 celestial planetary patterns*
 9637 (#) *Ephemeris has been searched for almost 250 top astronomical patterns of these 2500 configurations*
 9638 for mid-November 2017
 9639 (#) *There has been a significant match of most the patterns during this period. Range of search has been*
 9640 *narrowed to 2 days because exhaustive search for all patterns is intensive.*
 9641 (#) *This matches to NOAA CPC forecast in http://www.cpc.ncep.noaa.gov/products/JAWF_Monitoring/India/GFS_forecasts.shtml*
 9642
 9643 -----
 9644 466. (THEORY) Discrete Hyperbolic Computational Geometric Factorization, Chvatal Art Gallery Theorem
 9645 and Parallel Tiling - 6 November 2017, 8 November 2017 - related to 34
 9646 -----
 9647 Chvatal Art Gallery Theorem states for floodlighting an art gallery shaped as n-polygon, floor(n/3) guards are suffic
 9648
 9649 As opposed to polygon pixelation, if the hyperbolic curve is discretized into set of line segments by plain rounding
 9650
 9651 References:
 9652 -----
 9653 466.1 Chvatal Art Gallery Theorem and Fisk's Proof - <https://www.cut-the-knot.org/Curriculum/Combinatorics/Chvatal.shtml>
 9654 466.2 Number of prime factors of an integer - [Srinivasa Ramanujan] - Quarterly Journal of Mathematics, XLVIII, 1917,
 9655 466.3 Introduction to Parallel Algorithms - [Joseph JaJa] - Chapter 4 - Searching, Sorting, Merging - Corollary 4.5 - C
 9656
 9657 -----
 9658 467. (FEATURE-DONE) Support Vector Machines implementation - based on CVXPY - 9 November 2017
 9659 -----
 9660 (*) New Support Vector Machines python implementation is committed to NeuronRain AsFer repository
 9661 (*) This minimizes an objective function $1/2 * ||w||$ subject to constraint $||WX+b|| \geq 1$ which
 9662 labels a point +1 or -1 on either side of a decision separating hyperplane $WX+b$ for weight vector W
 9663 and bias b (Reference: Machine Learning - Ethem Alpaydin - Chapter 13 - Kernel Machines)
 9664 (*) Optimization is solved by CVXPY DCCP Convex-Concave program
 9665 (*) logs for this have been added to testlogs/
 9666 (*) Present NeuronRain AsFer SVMRetriever.cpp depends on third-party SVMlight opensource software. With
 9667 this new implementation, references to SVMlight are to be phased out.
 9668
 9669 -----
 9670 468. (THEORY) Random Matrix Rounding for CNFSAT Solver, Blum-Micali PRG, Distinguisher for Pseudorandomness - 10 Nove
 9671 related to 460
 9672 -----
 9673 Blum-Micali PRG depends on intractability of Discrete Logarithm $f(x)=g^x \bmod p$ for primes p,g and group element x. Bl
 9674 sequences of $(f(x), f^2(x), f^3(x), \dots)$ by composition of f and computes stream of bits by hard-core boolean predica
 9675
 9676 Probability of choosing a CNF by RMLSQR probability $(p=1/\sqrt{mn})$ and there are $3m$ literals per 3CNF = $(1/[mn])^{1.5m}$
 9677 Probability of choosing a CNF from all possible $n^{(3m)}$ random 3SATs in uniform distribution is = $(1/n)^{3m}$
 9678
 9679 Inverse of RMLSQR probability = $(mn)^{1.5m}$ is the expected number of pseudorandom binary strings churned out by PRG be
 9680 Inverse of uniform probability = n^{3m} is the expected number of pseudorandom binary strings churned out by PRG before
 9681
 9682 Distinguisher for these 2 distributions iterates through both sequences of bitstreams and prints "RMLSQR" if match oc
 9683
 9684 From PCP [Hastad] inapproximability result and previous Random Matrix analysis for approximate CNFSATsolver, if m^{3*r}
 9685
 9686 References:
 9687 -----
 9688 468.1 Existence of Pseudorandom Generators - [Goldreich-Hugo-Luby] - <http://www.wisdom.weizmann.ac.il/~oded/X/gkl.pdf>
 9689
 9690 -----
 9691 469. (FEATURE-DONE) Support Vector Machines - update - 10 November 2017
 9692 -----
 9693 (*) Numpy indexing has been changed
 9694 (*) Both random point and parametric point distances have been tested
 9695 (*) DCCP log and Support Vector logs for 2 points and a random point have been committed to testlogs/
 9696 (*) Distances are printed in the matrix result - two diametrically opposite points have equal distances

```

9697  (*) Distance matrix is returned from distance_from_separating_hyperplane() function
9698  (*) The distance minimized is the L1 norm (sum of tuple elements) and not L2 norm
9699  (sum of squares of tuple elements)
9700
9701
9702 470. (FEATURE-DONE) Computational Geometric Hyperbolic Factorization - Pixelated Segments Spark Bitonic Sort - Single
9703  Benchmarks - 13 November 2017
9704
9705  (*) Numbers 147,219,251,253 are factorized.
9706  (*) C++ tiling pre-processing routines have been changed for this and Pixelated Tiles storage text files for bitonic
9707  (*) Factorization is benchmarked on single node cluster on dual core (which is parallel RAM).
9708  (*) This is just a representative number on single dual-core CPU and not a cloud parallelism benchmark.
9709  (*) Each DAGScheduler Spark work item is independent code executable in parallel and benchmark has to be this parallel
9710  is captured in per task duration logs below by Spark Driver:
9711 17/11/13 21:18:22 INFO TaskSetManager: Finished task 1.0 in stage 1791.0 (TID 3583) in 46 ms on localhost (executor c
9712 17/11/13 21:18:22 INFO TaskSetManager: Finished task 0.0 in stage 1791.0 (TID 3582) in 47 ms on localhost (executor c
9713 17/11/13 21:18:22 INFO TaskSetManager: Starting task 0.0 in stage 1792.0 (TID 3584, localhost, executor driver, parti
9714 17/11/13 21:18:22 INFO TaskSetManager: Starting task 1.0 in stage 1792.0 (TID 3585, localhost, executor driver, parti
9715 17/11/13 21:18:22 INFO TaskSetManager: Finished task 1.0 in stage 1792.0 (TID 3585) in 46 ms on localhost (executor c
9716 17/11/13 21:18:22 INFO TaskSetManager: Finished task 0.0 in stage 1792.0 (TID 3584) in 50 ms on localhost (executor c
9717 17/11/13 21:26:39 INFO TaskSetManager: Finished task 0.0 in stage 1791.0 (TID 3582) in 50 ms on localhost (executor c
9718 17/11/13 21:26:39 INFO TaskSetManager: Finished task 1.0 in stage 1791.0 (TID 3583) in 49 ms on localhost (executor c
9719 17/11/13 21:26:39 INFO TaskSetManager: Starting task 0.0 in stage 1792.0 (TID 3584, localhost, executor driver, parti
9720 17/11/13 21:26:39 INFO TaskSetManager: Starting task 1.0 in stage 1792.0 (TID 3585, localhost, executor driver, parti
9721 17/11/13 21:26:39 INFO TaskSetManager: Finished task 0.0 in stage 1792.0 (TID 3584) in 48 ms on localhost (executor c
9722 17/11/13 21:26:39 INFO TaskSetManager: Finished task 1.0 in stage 1792.0 (TID 3585) in 49 ms on localhost (executor c
9723 17/11/13 21:33:59 INFO TaskSetManager: Finished task 0.0 in stage 1791.0 (TID 3582) in 48 ms on localhost (executor c
9724 17/11/13 21:33:59 INFO TaskSetManager: Finished task 1.0 in stage 1791.0 (TID 3583) in 50 ms on localhost (executor c
9725 17/11/13 21:33:59 INFO TaskSetManager: Starting task 0.0 in stage 1792.0 (TID 3584, localhost, executor driver, parti
9726 17/11/13 21:33:59 INFO TaskSetManager: Starting task 1.0 in stage 1792.0 (TID 3585, localhost, executor driver, parti
9727 17/11/13 21:33:59 INFO TaskSetManager: Finished task 0.0 in stage 1792.0 (TID 3584) in 55 ms on localhost (executor c
9728 17/11/13 21:33:59 INFO TaskSetManager: Finished task 1.0 in stage 1792.0 (TID 3585) in 57 ms on localhost (executor c
9729 17/11/13 21:40:20 INFO TaskSetManager: Finished task 1.0 in stage 1791.0 (TID 3583) in 49 ms on localhost (executor c
9730 17/11/13 21:40:20 INFO TaskSetManager: Finished task 0.0 in stage 1791.0 (TID 3582) in 52 ms on localhost (executor c
9731 17/11/13 21:40:20 INFO TaskSetManager: Starting task 0.0 in stage 1792.0 (TID 3584, localhost, executor driver, parti
9732 17/11/13 21:40:20 INFO TaskSetManager: Starting task 1.0 in stage 1792.0 (TID 3585, localhost, executor driver, parti
9733 17/11/13 21:40:20 INFO TaskSetManager: Finished task 0.0 in stage 1792.0 (TID 3584) in 50 ms on localhost (executor c
9734 17/11/13 21:40:20 INFO TaskSetManager: Finished task 1.0 in stage 1792.0 (TID 3585) in 50 ms on localhost (executor c
9735
9736  (*) Bitonic Sort is  $O(\log N * \log N)$  and number of processors required is approximately  $O(N^{2.5})$  but abides by NC definit
9737
9738
9739 471. (FEATURE-DONE) Support Vector Machines Update - Learn and Classify functions - 13 November 2017
9740
9741  (*) Support Vector Machines python implementation has been updated to include two functions :
9742      - for learning set of support vectors from a training dataset tuples and store the vectors in a dictionary ma
9743      - to classify a tuple by finding its distance with reference to the support vector regions - distance-to-vect
9744      - if there are more than 1 tuples per minimum distance, those have to be reckoned as support vectors
9745
9746
9747 472. (THEORY) Jones-Sato-Wada-Wiens Theorem, Complement Functions, Prime-Composite Complementation, Prime Number Thec
9748  Ramsey 2-coloring of integers, Hilbert Tenth Problem, Unique Factorization , Matiyasevich-Robinson-Davis-Putnam Theor
9749  related to 24,370,390,394 - 13 November 2017, 14 November 2017, 29 November 2017, 1 December 2017, 4 December 2017, 23 C
9750  (Draft updates to https://arxiv.org/abs/1106.4102)
9751
9752  Jones-Sato-Wada-Wiens Theorem proves existence of a polynomial in 25 degree-26 variables which has values equal to se
9753
9754  Number of primes < p=xy:
9755      = c1*xy/logxy
9756  Number of primes < q=(x+1)y:
9757      = c1*(x+1)y/log(x+1)y
9758
9759  Number of primes between p=xy and q=(x+1)y :
9760      = c1*(x+1)y/log(x+1)y - c1*xy/logxy
9761
9762  Assuming number of primes between p and q = c1*(x+1)y/log(x+1)y - c1*xy/logxy > 0:
9763      (x+1)y/log(x+1)y > xy/logxy
9764  After reducing:
9765      log(xy) > x(log(x+1) - logx)
9766      log(xy) > xlog(x+1/x)
9767  For large x:
9768      log(x+1/x) ~ log 1 = 0
9769  =>      log(xy) > 0
9770  thus proving the assumption. This estimate of number of primes between two composites thus directly has bearing on di
9771
9772  Matiyasevich-Davis-Robinson-Putnam theorem implies every recursively enumerable set has a diophantine equation. Compl
9773
9774  Definition:
9775
9776  For a set S and subsets A,B of S, if {A,B} is a disjoint set cover of S and if A has a diophantine equation diophanti
9777

```

```

9778 -----
9779 Theorem: Existence of Complement Diophantine Equation or Complement Function is Undecidable when neither of the compl
9780 -----
9781 Proof:
9782 -----
9783 MRDP theorem for Hilbert's tenth problem implies every recursively enumerable set is expressible as values of a dioph
9784 -----
9785 Possibility 1 - Generic - Both complementary sets A and B are recursively enumerable:
9786 -----
9787 If both complementary sets A and B are recursively enumerable, they always have a diophantine polynomial - diophantir
9788 There is a known result which states: if set A and B=S-A are both recursively enumerable, then A is recursive. But th
9789 -----
9790 Possibility 2 - Special - One of the complementary sets A or B is recursively enumerable and the other is recursive:
9791 -----
9792 Both A and B have a diophantine polynomial. If A is recursively enumerable but not recursive, there is a complement E
9793 -----
9794 Possibility 3 - Special - Both complementary sets A and B are recursive:
9795 -----
9796 Both A and B are recursive and recursively enumerable => Both A and B have diophantine polynomials and both diophanti
9797 -----
9798 Possibility 4 - Special - Both complementary sets are non recursively enumerable:
9799 -----
9800 Obviously both sets A and B are beyond Chomsky hierarchy and there is no algorithm for construction of diophantine(A)
9801 -----
9802 Possibility 5 - Special - One of the complementary sets is recursively enumerable and the other is non recursively er
9803 -----
9804 One of the sets A is recursively enumerable and thus has a diophantine polynomial. But there exists a complement B=S-
9805 -----
9806 Proof in one line: Any set is a complementary set of some other set and thus any complementary set which is recursive
9807 -----
9808 Construction of a complement function for complementary set:
9809 -----
9810 Construction of a complement function is to find a mapping function f defined as:
9811   f(0) = a1
9812   f(1) = a2
9813   f(2) = a3
9814   ...
9815   f(n) = an
9816 for a1,a2,a3,...,an in Diophantine complementary set, which is equivalent to definition of recursively enumerable tot
9817   f(x) - a = 0
9818 Function f can internally be any mathematical function and can have additional parameters besides x. Finding the enum
9819 -----
9820 An important example for applicability of function complementation is ABC Conjecture which is defined in references b
9821 -----
9822 References:
9823 -----
9824 472.1 Jones-Sato-Wada-Wiens Theorem and Prime valued Polynomial - https://www.maa.org/sites/default/files/pdf/upload\_472.1.pdf
9825 472.2 Matijasevic Polynomial - http://primes.utm.edu/glossary/xpage/MatiyasevicPoly.html - negative values can be ren
9826 472.3 Hilbert's Tenth Problem and Matiyasevich-Robinson-Davis-Putnam (MRDP) Theorem - https://en.wikipedia.org/wiki/Hilbert's\_tenth\_problem
9827 472.4 Primes are nonnegative values of a polynomial in 10 variables - [Yu.V.Matiyasevic - https://logic.pdmi.ras.ru/~matijasevic/]
9828 472.5 Pell's Equation - https://en.wikipedia.org/wiki/Pell%27s\_equation - Diophantine equation for set of nonsquare i
9829 472.6 Non-Recursively Enumerable Languages - https://www.seas.upenn.edu/~cit596/notes/dave/relang8.html - powerset o1
9830 472.7 Goedel's First Incompleteness Theorem Follows From MRDP theorem - https://en.wikipedia.org/wiki/Goedel%27s\_incompleteness\_theorem
9831 472.8 What is Mathematics: Goedel Theorem and Around - https://dspace.lu.lv/dspace/bitstream/handle/7/5306/Podnieks\_k%20-%20Goedel.pdf
9832   (*) Is set B recursively enumerable? (There are sets which are not recursively enumerable e.g set of subsets c
9833   (*) If set B is recursively enumerable, B has an equivalent diophantine polynomial. But there exists a set B w
9834   (*) In both possibilities, there is a set which does not have a diophantine polynomial - there is a non-recurs
9835 472.9 Goedel Incompleteness and MRDP theorem - https://plato.stanford.edu/entries/goedel-incompleteness/#HilTenProMRL\_MRDP\_Theorem
9836   There is no general method for deciding whether or not a given Diophantine equation has a solution. ..
9837 472.10 Special Case of Complement Functions and MRDP Theorem - http://www.logicmatters.net/resources/pdfs/MRDP.pdf
9838 472.11 MRDP Theorem, Jone-Sato-Wada-Wiens Polynomial and Undecidability in Number Theory - [Bjorn Poonen] - http://www.math.mit.edu/~poonen/papers/mrdp.pdf
9839 472.12 Formulas for Primes - https://oeis.org/wiki/Formulas\_for\_primes#Solutions\_to\_Diophantine\_equations
9840 472.13 Simplest Diophantine Representation - [Panu Raatikainen] - https://pdfs.semanticscholar.org/cd96/ead1a00b73ecc
9841 472.14 Waring Problem and Diophantos/Bachet/Lagrange Four Square Theorem for real quaternions - Topics in Algebra -
9842 472.15 Complement Functions, Diophantine Analysis and ABC Conjecture - https://en.wikipedia.org/wiki/ABC\_conjecture - Let a + b = c be a mutually coprime integer triple f(a,b,c). Quality q(a,b,c) is defined as = log(c)/log(radical(abc))
9843 472.16 Erdos-Straus Diophantine Conjecture - https://en.wikipedia.org/wiki/Erd%C5%91s%20%93Straus\_conjecture - For
9844 472.17 ABC Conjecture Proof-designate - Interuniversal Teichmuller Theory - [Shinichi Mochizuki] - http://www.kurims.kyoto-u.ac.jp/~mochi/abc/
9845 472.18 Exponential Diophantines, Fibonacci and Lucas Sequences, Maximum limit on solvability of Diophantine - Reducti
9846 473. (FEATURE-DONE) Support Vector Machines Update and Discrete Hyperbolic Factorization Spark Benchmarks
9847 - 14 November 2017
9848 -----
9849 -----
9850 (*) Support Vector Machines implementation has been updated to persist the learnt support vectors to
9851 a disk file SupportVectorMachines.txt
9852 (*) This text file is read in classify()
9853 (*) Support Vectors Dictionary is JSON dumped and eval()-ed and not JSON loaded because of serialization
9854   glitch in defaultdict(list)
9855 -----
9856 -----
9857 -----
9858 -----

```

```

9859 (*) Computational Geometric Hyperbolic Factorization Spark implementation has been benchmarked for
9860 2 more integers of 9 and 10 bits. Some 8 bit numbers were benchmarked earlier.
9861 (*) Spark logs for these benchmarks have been committed and time duration is calculated as 3 way split
9862 of real/user/system by time shell utility
9863 (*) These benchmark numbers are on dual core single node Spark cluster
9864 (*) C++/python files for tilings have been updated and pixelated tiles storage text files have been rewritten
9865 -----
9866 Note on Factorization Spark benchmarks
9867 -----
9868 Following are approximate correlations of the observed numbers to the theoretical polylogarithmic time bound - expone
9869
9870 10 bit - real 17m11.931s = 1031.931s (-k*10^x3) ~ (logN)^3.013 (x3=3.013)
9871 9 bit - real 7m46.247s = 466.247s (-k*9^x2) ~ (logN)^2.796 (x2=2.796)
9872 8 bit - real 3m40.091s = 220.091s (-k*8^x1) ~ (logN)^2.589 (x1=2.589)
9873 8 bit - real 3m39.539s = 219.539s (-k*8^x1) ~ (logN)^2.589 (x1=2.589)
9874 8 bit - real 3m38.795s = 218.795s (-k*8^x1) ~ (logN)^2.589 (x1=2.589)
9875 8 bit - real 3m38.622s = 218.622s (-k*8^x1) ~ (logN)^2.589 (x1=2.589)
9876 8 bit - real 3m38.920s = 218.920s (-k*8^x1) ~ (logN)^2.589 (x1=2.589)
9877 -----
9878 -----
9879 474. (THEORY) Computational Geometric Hyperbolic Factorization, Discrete Geometry, Rastering in Graphics/Computations
9880 Bresenham's Line Algorithm adapted for Hyperbolic tiling, Point Location, Ray shooting - 15,16 November 2017 - relate
9881 -----
9882 Finding factors of integer N by creating pixelated polygon for hyperbolic curve xy=N has great visual intuition. Simi
9883 exist in discrete geometry and computer graphics disciplines. Bresenham's Line drawing algorithm is a classic used st
9884 which approximates a continuous line on a pixelated digital space. This approximation of continuous curves on digital
9885 Rastering. Tile segments of hyperbola in preprocessing step of factorization are found by solving for deltax in:
9886     xy = N
9887     (x+1)(y-deltay) = N
9888     xy - x*deltay + y - deltay = N
9889     y = deltay * (x+1)
9890     deltay = y/(x+1) for deltax=1
9891 which is similar to Bresenham Line algorithm for finding next point to plot on raster. Tile segment (N/x, N/(x+1)) al
9892 interval (y, y-(y/x+1)) on y-axis.
9893
9894 Tiling preprocessing phase of factorization embeds a continuous hyperbola in a grid of horizontal and vertical straig
9895 line corresponds to an integer in y-axis and vertical line to an integer in x-axis. Hyperbolic arc traverses the squ
9896 Thus the polygon approximating the continuous hyperbola is the union of all squares(pixels) through which hyperbolic
9897 squares create rectangular faces of the art gallery polygon vertices of which are the locations of the guards. Vertic
9898 through which hyperbolic arc passes through are the factors.
9899
9900 Art Gallery Pixelated polygon approximating a hyperbola is a Planar Simple Line Graph (PSLG) where each side of the p
9901 PSLG. This PSLG has (number_of_factors + 1) rectangular faces which is O(loglogN). Vertices where two adjacent recta
9902 meet are the factor points of N. Planar point location has to find these factor points. Geometric Ray Shooting Query
9903
9904 References:
9905 -----
9906 474.1 Bresenham Algorithm for Line Rastering - https://en.wikipedia.org/wiki/Bresenham%27s\_line\_algorithm
9907 474.2 Rasterizing curves - http://members.chello.at/easyfilter/bresenham.pdf
9908 474.3 Efficient Algorithms for Ray Shooting Queries - [Pankaj K. Agarwal] - https://pubs.siam.org/doi/pdf/10.1137/022
9909 474.4 Parallel Planar Point Location - [Richard Cole] - https://ia601408.us.archive.org/33/items/onoptimalparallel00cc
9910 474.5 Parallel Geometric Search - [Albert Chan, Frank Dehne, Andrew Rau-Chaplin] - https://web.cs.dal.ca/~arc/publicat
9911 474.6 Parallel Computational Geometry - https://www.cs.princeton.edu/~chazelle/pubs/ParallelCompGeom.pdf - [A. Aggarwal]
9912
9913 -----
9914 475. (FEATURE-DONE) Computational Geometric Factorization - Tiling Update and benchmark numbers for factoring few int
9915 -----
9916 (*) Existing hyperbolic tiling code depends on C++ code in cpp-src/miscellaneous
9917 (*) To remove this dependency, python script for tiling the hyperbolic arc with simple pixelation similar to bresenh
9918 (*) This function is invoked in DiscreteHyperbolicFactorizationUpperbound_Bitonic_Spark.py before bitonic sort
9919 (*) DiscreteHyperbolicFactorizationUpperbound_Bitonic_Spark.py is parametrized and accepts number to factorize as com
9920     ##$SPARK 2.1.0 HOME/spark-submit DiscreteHyperbolicFactorizationUpperbound_Bitonic_Spark.py <number_to_factoriz
9921 (*) Few more time shell builtin benchmark numbers for factorizing 3-bit, 4-bit, 5-bit, 6-bit, 7-bit integers have be
9922
9923 -----
9924 476. (FEATURE-DONE) Computational Geometric Factorization Update - Spark Accumulators, JSON for Tiling etc., - 19 Nov
9925 -----
9926 (*) Hyperbolic tiling code in python has been changed to reflect C++ tiling in cpp-src/miscellaneous
9927 (*) globalcoordinates global variable has been made Spark Accumulator Mutable global state - globalmergedtiles is alr
9928 (*) bitoniclock acquire/release statements have been added for global variables, but commented for benchmarking
9929 (*) New boolean flags for bitonic comparator python style variable swap, for enabling multiple threads for assign hav
9930 (*) merge_sorted_halves() has been invoked as a separate function
9931 (*) C++ tiling has been chosen because accuracy of long double in creating tile pixels is better than similar tiling
9932 (*) Benchmark numbers for factoring 511 has been added to testlogs/ and are similar to previous numbers
9933 (*) .mergedtiles and .coordinates files are loaded/dumped as JSON in python hyperbolic tiling
9934
9935 -----
9936 477. (FEATURE-DONE and THEORY) Computational Geometric Factorization Update - Benchmarks and Tiling - 20 November 201
9937 -----
9938 (*) Some further changes to Python hyperbolic tiling have been made - tile endpoints have been cast from floating poi
9939 for create_tile()

```

```

9940  (*) C++ tiling in cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_Bitonic.cpp has been parametrized as
9941  as commandline argument the integer to factorize.
9942  (*) Shell script cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_Bitonic.sh has been changed to pass
9943  factorize to the C++ tiling binary in cpp-src/ and spark-submit for PySpark executable in python-src/ from shell args
9944  (*) This shell script unifies C++ tiling and PySpark factorization
9945  (*) Known issues: Python tiling still differs from C++ tiling significantly. Changing the hardcoded tile arrays stored to
9946  malloc()-ed heap storage causes faulty tiling. There are only optimization issues which do not affect the factorization
9947  works well and more benchmarks were done e.g for integers 723 and 501. Numbers for these and past numbers are charted
9948  (*) Following profiling numbers along with previous benchmarks for 8,9,10 bits (14 November 2017) capture the trend in
9949  (*) Gradual increase in exponent of number of bits because of static number of parallel RAMs (cores) is not quite the
9950  3-bit to 10-bit integers as one might expect. Integers of same bit numbers need almost equal duration to factorize which
9951  could be a function of logN and not N. Htop shows equal loading of both cores of CPU and consumption is almost 100%+1
9952  (*) Cloud computing is not exactly a parallel RAM but multiple cores are PRAMs having concurrent access to a shared memory
9953  cloud have local memory processing too. Spark's Global State Variables (Accumulators) which are reflected across all
9954  software simulations of Parallel RAMs - same global state is concurrently accessed by CPUs of spark nodes. Present Py
9955  does the sorting on accumulators. Binary search is not necessary because Maximum elements at the end of the k-merge
9956  is an update to drafts in 34.1 and 34.2:
9957      - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization/
9958      - http://sourceforge.net/projects/acadpdrafts/files/DiscreteHyperbolicPolylogarithmicSieveForIntegerFactorization/
9959
9960  (*) Following are only representative figures and ideal benchmark requires a Spark cloud preferably on machines of high
9961  and comparison with existing General Number Field Sieve implementations (which is quasipolynomial-exponential).
9962
9963  723 - 10-bit - real 16m30.346s = 990.346s ~ 0(logN^2.9956)
9964  511 - 9-bit - real 7m46.518s = 466.518s ~ 0(logN^2.8382)
9965  511 - 9-bit - real 7m35.642s = 455.642s ~ 0(logN^2.7854)
9966  501 - 9-bit - real 7m36.879s = 456.642s ~ 0(logN^2.7864) [shell script - includes time duration for C++ tiling]
9967  100 - 7-bit - real 2m33.911s = 153.911s ~ 0(logN^2.5851)
9968  123 - 7-bit - real 2m52.704s = 172.704s ~ 0(logN^2.6482)
9969  63 - 6-bit - real 1m17.460s = 77.460s ~ 0(logN^2.4243)
9970  33 - 6-bit - real 0m58.950s = 58.950s ~ 0(logN^2.2757)
9971  14 - 4-bit - real 0m19.927s = 19.927s ~ 0(logN^2.1609)
9972  12 - 4-bit - real 0m19.651s = 19.651s ~ 0(logN^2.1609)
9973  6 - 3-bit - real 0m15.118s = 15.118s ~ 0(logN^2.4649)
9974
9975
9976  478. (THEORY) Computational Geometric Factorization - Tiling Optimizations - K-Merge Sort is dispensable and Local Tile Sort
9977  - 21 November 2017
9978
9979  Finding factor vertices in pixelated hyperbolic polygon is equivalent to geometric search query: "Is there a right turn or
9980  downturn in the polygon?". These turning points coinciding with hyperbolic arc are factor points. Number of rectangle
9981  polygon = O(loglogN). Each tile along y-axis in the polygon (array of pixels) is of length deltax = N/[x(x+1)]. Maxim
9982  in the pixelation can be derived as:
9983      xy=N
9984      (x+deltax)(y-deltay)=N
9985      => xy + y*deltax - x*deltay - deltax*deltay = N
9986      But deltax = 1,
9987      => y - (x+1) deltax = 0
9988      deltax = y/(x+1) and y = N/x
9989      => N/x(x+1) = deltax > 1 [each tile should be of length atleast 1]
9990      N > x*x + x
9991      => x = (sqrt(1 + 4N) - 1) / 2
9992      For large N, sqrt(1 + 4N) ~ sqrt(4N) = 2*sqrt(N)
9993      => x ~ sqrt(N) for large N
9994  Maximum number of tiles in the pixelation is O(sqrt(N)). If number of processors is O(sqrt(N)), each tile can be assigned
9995  tiling can be done in O(1) parallel time. Number of processors required can be reduced by having O(sqrt(N)/(logN)^c) tiles
9996  can be created in O((logN)^c) total parallel time i.e in each iteration O(sqrt(N)/(logN)^c) tiles can be created
9997
9998  Thus factors can be found just by:
9999      478.1 Tiling in parallel requiring O((logN)^c) tile and O(sqrt(N)/(logN)^c) processors where number of tiles
10000      478.2 Local Binary Search per processor on each sorted tile of O(logN) time
10001  and no k-merge sort is necessary.
10002
10003  Previous optimization reduces number of PRAMs by orders of (logN)^c but increases exponent of parallel time O((logN)^c)
10004
10005  References:
10006
10007  478.1 Line segment turn detection - http://fileadmin.cs.lth.se/cs/Personal/Rolf\_Karlsson/lect9.pdf - For two line segments, cross product of adjacent pairs of line segment vectors can be computed in
10008  its sides as input array of line segments, cross product of adjacent pairs of line segment vectors can be computed in
10009  478.2 Sweepline algorithms - http://www.ics.uci.edu/~goodrich/pubs/ggb-sweep-j.pdf
10010  478.3 Rectangle Stabbing - School on Geometric Computing, IIT Delhi (2010) - http://www.cse.iitd.ernet.in/~ssen/geoms/
10011
10012
10013  479. (FEATURE-DONE and THEORY) Computational Geometric Factorization and Parallel Tile Search Updates
10014  - related to 34 and 478 - 22 November 2017
10015
10016  (*) cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_Bitonic.cpp has been revamped and unnecessary code
10017  (*) New Spark python script python-src/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.py has been added
10018  (*) How Spark parallelizes a sequential datastructure on cloud nodes is equivalent to binary search on an array of length
10019  (*) Benchmark numbers for two integers 1011 and 1013 with and without sorting have been committed to testlogs/ and Ti
10020  (*) As evidenced from python-src/testlogs/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.log.22Novem

```

```

10021  (*) Benchmarks for Local Tile Search obviate the requirement for k-merge sorting of pixelated hyperbolic tiles, if pa
10022  (*) Following is the trade-off:
10023      - Bitonic K-merge sorting of tiles : binary search is not necessary but a tremendous performance drag and ove
10024      - Local tile search : binary search is necessary only per processor but requires relatively high number of PR
10025
10026 -----
10027 480. (FEATURE-DONE) Computational Geometric Factorization Tiling Optimization - Binary Search for Tile Segments in Sp
10028 -----
10029  (*) Binary Search has been implemented in Spark Tile Search Optimization by parallelizing the set of intervals of pixel
10030  (*) By this each tile interval can be binary searched in parallel to find the factor point with no
10031  necessity for global k-merge sorting.
10032  (*) Separate pixelation and tile interval file creation C++ source file has been added in cpp-src/miscellaneous
10033  (*) Arrayless tile creation has been chosen and only intervals are written to a file suffixed as .tileintervals
10034  (*) Shell script which compiles and executes the tile interval creation file and spark interval binary search script
10035  (*) Invoking the shell script as:
10036      cpp-src/miscellaneous/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.sh <number_to_factorize>
10037  is sufficient to print the factors
10038  (*) Following are benchmark numbers for factorizing few reasonably high bit integers. Removing K-Merge sort has signi
10039  throughput even for a single node spark cluster on dual core (local[2]):
10040
10041 Factorization of 12093 (14-bit): real 0m29.589s (dual core - local[2])
10042
10043 Factorization of 65532 (16-bit): real 0m44.899s (single core - local[1])
10044 Factorization of 65532 (16-bit): real 0m39.621s (dual core - local[2])
10045
10046
10047 Factorization of 102349 (17-bit): real 1m5.490s (single core - local[1])
10048 Factorization of 102349 (17-bit): real 0m58.776s (dual core - local[2])
10049
10050 Factorization of 934323 (20-bit): real 8m20.017s (single core - local[1])
10051 Factorization of 934323 (20-bit): real 7m37.958s (dual core - local[2])
10052
10053 Factorization of 1343231 (21-bit): real 16m34.759s (single core - local[1])
10054 Factorization of 1343231 (21-bit): real 10m49.218s (dual core - local[2])
10055
10056  (*) Above tile binary search numbers beat bitonic k-mergesort of tiles by many orders of magnitude
10057  (*) logs containing factors of above integers have been committed to testlogs/
10058  (*) This optimization thus effectively supersedes mergesort of tiles and is thus a better PySpark implementation of C
10059 -----
10060  (*) Updated AsFer Design Document - benchmark numbers for both single and dual cores for tile search
10061  in computational geometric factorization
10062  (*) Updated python-src/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.py for dual cores
10063  (local[2])
10064
10065 -----
10066 481. (FEATURE-DONE) Computation Geometric Factorization - Binary Search for Tiles - Benchmarks
10067  - 24 November 2017
10068 -----
10069  Benchmark numbers for factoring 24 bit integer by Tile BinarySearch Optimization script have been committed to testlc
10070
10071 Factorization of 9333123 (24-bit):
10072 -----
10073  real 112m24.101s (Spark duration 12:21 to 14:02 = 101minutes = 6060seconds)
10074  user 0m0.000s
10075  sys 0m0.004s
10076
10077 Again binary search of tiles in parallel is way better than k-mergesort of tiles. Largest known numbers
10078  widely used are 128-bit. Trend for different bits indicates, Spark cloud of few multicore nodes is
10079  sufficient to factorize 128-bit integers in few minutes. Previous benchmark uses spark-default.conf files
10080  from python-src/InterviewAlgorithm/ (2GB of heapspace)
10081
10082
10083 482. (THEORY) Computational Geometric Factorization - Parallel Local Binary Search for Tiled Hyperbolic Arc - 27 Nove
10084  - Snir's Theorem for Parallel Search - related to 34,478
10085 -----
10086 Previous optimized factorization with no sorting and only local binary search per tile interval can achieve further s
10087
10088 Tiling preprocessing of hyperbolic arc creates O(N) tiles. [This is proportional to length of hyperbolic arc obtainable
10089  calculus = DefiniteIntegral(sqrt(1 + [N^2/x^4]))]
10090
10091 Number of iterations = O((logN)^k)
10092 Number of PRAMs = (N/(logN))^k
10093
10094 Factorization in parallel has following algorithm:
10095 while(iterations <= O((logN)^k))
10096 {
10097     *) Assign N/(logN)^k tiles to N/(logN)^k PRAMs in parallel (O(1) parallel time because each interval tile in a
10098     *) Binary Search tile in each PRAM for factors (O(logN) parallel time which can be reduced to O(logN/logp) by
10099 }
10100
10101 Previous loop totally is of [O(1) + O(logN)]*O((logN)^k) = O((logN)^(k+1)) parallel time. For minimum value of k=1, F

```

10102 local binary search of tiled hyperbolic arc, can be done in $O((\log N)^2)$ parallel time and $O(N/\log N)$ PRAM processors w
 10103 $O(\log N * \log N / \log p)$ in CREW PRAM.

10104

10105 References:

10107 482.1 Efficient Parallel Algorithms and subclasses of NC - [KruskalRudolphSnir] - <https://ac.els-cdn.com/030439759096>
 10108 482.2 On Parallel Search - Snir's Theorem - <https://pdfs.semanticscholar.org/3a58/58e8517f28fa586364daffb34160c437bf>
 10109 482.3 Point in Polygon (PIP) problem - https://en.wikipedia.org/wiki/Point_in_polygon - queries if a point is inside,
 10110 482.4 Simulation of BSP and CRCW PRAM in MapReduce - Sorting, Searching, and Simulation in the MapReduce Framework -
 10111 482.5 Models of Parallel Computation - PRAM shared memory model can be simulated on BSP distributed memory model - ht
 10112 482.6 PRAM memory access is unit time - [Guy Blelloch] - <http://www.cs.cmu.edu/afs/cs/academic/class/15499-s09/www/sc>

10113

10114

10115 -----

10116 483. (FEATURE-DONE) Support Vector Machines - Mercer Theorem - Kernel Implementation - 29 November 2017

10117 -----

10118 (*) This commit implements the kernel trick for lifting points in lower dimension to higher dimension by a Feature ma
 10119 decision hyperplane in higher dimension separates the points accurately.

10120 (*) Mercer Theorem creates a kernel function unifies Feature map lifting and Dot product in higher dimension

10121 (*) Feature map phi maps a point in a dimension d to a point in dimension d+k: $\phi(x) = X$. Inner Product (Dot) of two
 10122 $d+k = \phi(x) \cdot \phi(y)$. Mercer Theorem unifies the Feature map and Dot product into a Kernel function defined as series:
 $K(x,y) = \sum_i (\text{eigenvalue}(i) \cdot \text{eigenfunction}(x) \cdot \text{eigenfunction}(y))$

10123 (*) This implementation randomly instantiates a $N \times N$ square matrix, finds its Eigenvalues and Eigenvectors, and comput
 $K(x,y)$ as per previous identity (neglecting imaginary parts of Eigenvalues and Eigenvectors)

10124 (*) logs for this have been added to testlogs/

10125

10126 -----

10127 484. (FEATURE-DONE) Support Vector Machines - Mercer Kernel Update - 30 November 2017

10128 -----

10129 (*) Mercer Kernel Function has been changed to return a tuple of feature mapped points and the dot product

10130 (*) Feature mapped points in higher dimension are : $[\dots, \sqrt{\text{eigenvalue}[i]} \cdot \text{eigenfunction}(x[i]), \dots]$

10131

10132 -----

10133 485. (FEATURE-DONE) Compressed Sensing - Image Sketch implementation - 1 December 2017

10134 -----

10135 (*) Sketch B of an image bitmap X is computed by multiplying with a random matrix A: $B = AX$

10136 (*) import ImageToBitMatrix from image_pattern_mining/ for mapping an image to a bitmap matrix

10137 (*) Sketch matrix B contains compressed information of the larger image. Original image can be sensed from this sketc

10138

10139 -----

10140 486. (FEATURE-DONE) Compressed Sensing Update - Decompression and Error estimation of recovered image bitmap from ske

10141 -----

10142 (*) Sketch $AX = B$ of an image bitmap has been persisted to a file CompressedSensing.sketch

10143 (*) A is a random matrix of dimensions (m, n) $m \ll n$ and m is scaled by a sketch ratio variable

10144 (*) Original image x is recovered from sketch $AX = B$ by inverting A and multiplying with sketch:
 $A^{-1} \cdot AX = A^{-1} \cdot B$

10145 (*) For non-square only approximate pseudo inverse is computable.

10146 (*) For inverting non-square matrix A, Moore-Penrose Pseudoinverse function pinv() from NumPy is invoked.

10147 (*) Error of the recovered image computed by trace (sum of all entries) of the recovered image.

10148 (*) Logs for multiple sketch ratios (row values: 100, 200, 300, 400, 50) have been committed to testlogs/ which show an in
 as size of the sketch decreases.

10149

10150 -----

10151 487. (THEORY) Computational Geometric Factorization, Tile Search Optimization and Parallel Interval/Segment Search Tr
 10152 and 22 December 2017 - related to 34, 482

10153 -----

10154 Tile Search optimization for finding factors of an integer described earlier, binary-search set of intervals in paral
 10155 This is the classic segment/interval search tree problem in Computational Geometry. Segments/Intervals are 1-dimensic

10156

10157 Unique Prime Factorization of an integer $N = p_1^{k_1} * p_2^{k_2} \dots * p_n^{k_n}$

10158 This can be rewritten as:

10159
$$2^{\log N} = 2^{(k_1 \log(p_1) + k_2 \log(p_2) + \dots + k_n \log(p_n))}$$

10160
$$\Rightarrow \log N = (k_1 \log(p_1) + k_2 \log(p_2) + \dots + k_n \log(p_n))$$

10161 SmallOmega(N) = number of distinct prime factors of $N = O(\log \log N)$ from Hardy-Ramanujan Theorem

10162 BigOmega(N) = number of prime factors including multiplicity = sum of prime powers = $k_1 + k_2 + k_3 + \dots + k_n$

10163 But $k_1 + k_2 + k_3 + \dots + k_n < (k_1 \log(p_1) + k_2 \log(p_2) + \dots + k_n \log(p_n)) = \log N$

10164 $\Rightarrow \text{BigOmega}(N) < \log N$

10165 $\text{BigOmega}(N) = O(\log N)$ [This is very high upperbound and not tight estimate]

10166

10167 Segment binary search tree representation of pixelated hyperbolic tile segments is described in references below.

10168

10169 Factorization algorithm for N based on Segment Tree Search is:

10170
$$\begin{aligned} & (\#) \text{ Construct Segment Tree of Pixelated Hyperbolic Segments in Parallel } O(\log N) \text{ or between } O((\log N)^2) \text{ and } O(N) \\ & (\#) \text{ Query the Segment Tree for factor points in } O(k + \log N) \text{ where } k \text{ is the number of segment intervals to be } \end{aligned}$$

10171

10172 Thus there are 3 Computational Geometric Factorization algorithms described in this draft and all of them are PRAM al

10173
$$\begin{aligned} & (\#) K\text{-MergeSort and BinarySearch of Hyperbolic tile segments (mentioned in 34 - requires merge sort of tile i)} \\ & (\#) \text{ Local Binary Search in parallel of hyperbolic tiles without K-MergeSort (mentioned in 481 - recent optimi} \\ & (\#) \text{ Segment Tree Representation and Binary Search of hyperbolic tile Segments (uses a classic datastructure,} \end{aligned}$$

10174

10175 Note: First and Third factorization algorithms are equivalent because both involve sorting of pixelated hyperbolic ti

10176

10177

10178

10179

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10182

```

10183 An Unsorted Search algorithm has been implemented in NeuronRain (Section 500) to locate a query point on an unsorted
10184 Length of each tile on x-axis can be derived from equating for N:
10185      $xy = (x+\delta)(y-1)$ 
10186      $\delta = x/(y-1) = N/(y(y-1))$ 
10187
10188 Sum of lengths of all pixelated hyperbolic tiles along x-axis is the series:
10189      $N/(1^2) + N/(2^2) + N/(3^2) + \dots$ 
10190 But:
10191      $N/(1^2) + N/(2^2) + N/(3^2) + \dots < N/1 + N/2^2 + N/3^2 + \dots < N + \text{DefiniteIntegral}_2 \text{ to } N(dx/x^2) = 1.5N-1$ 
10192 => Sum of lengths of all pixelated hyperbolic tiles is upperbounded by  $1.5N-1$  or  $O(N)$ 
10193
10194 Some more optimizations:
10195 -----
10196 [##] Sorting is required only if end points of two adjoined segments are in conflict (only some, not all, elements in
10197
10198 [Subsegment1] Elements of succeeding tile segment become bigger than last element in preceding tile segment if:
10199      $xy < (x + \delta)(y-1)$ 
10200      $xy < xy - x + \delta(y-1)$ 
10201     =>  $\delta > x/(y-1)$ 
10202
10203 [Subsegment2] Similarly first element in succeeding tile is bigger than last element in Subsegment1 if:
10204      $(x+\delta)y < (x + N/(y-1)(y-2))(y-1)$ 
10205
10206 Splitting each tile segment of length  $l$  into two subsegments of length  $\delta$  and  $l-\delta$  and binary searching two set
10207
10208 [##] If the quadrant containing hyperbolic arc is partitioned by parallel ray shooting queries from origin, separated
10209      $y(m) = \text{SquareRoot}(N/[\tan(m^*\pi/(2^*k^*\log\log N))]) - 1$  for  $m=1,2,3,\dots,k\log\log N$ 
10210 These are only approximate angles. Factors should lie in close proximity of the intersection points of these rays wit
10211
10212 References:
10213 -----
10214 487.1 Parallel Segment Trees - [AV Gerbessiotis] - https://web.njit.edu/~alegx/pubs/papers/segment.ps.gz
10215 487.2 Distributed Segment Trees - [Guobin Shen, Changxi Zheng, Wei Pu, and Shipeng Li - Microsoft Research] - http://
10216 487.3 Computational Geometry - Algorithms and Applications - [Mark de Berg, Otfried Cheong, Marc van Kreveld, Mark Ov
10217 487.4 Parallel Construction of Binary Search Trees - [MJA tallah, SRKosaraju, LLLarmore, GLMiller, SHTeng] - https://www.c
10218 487.5 Segment Trees - definition and diagrams - [Computational Geometry Course Notes - Antoine Vigneron - King Abdull
10219 487.6 Hardy-Ramanujan Theorem - https://en.wikipedia.org/wiki/Hardy%20%80%93Ramanujan\_theorem
10220 487.7 Parallel Construction of Segment Trees - https://www.cs.dartmouth.edu/~trdata/reports/TR92-184.pdf - [Peter Su,
10221 487.8 Parallel Computational Geometry - Parallel Construction of Segment Trees is  $O(\log N)$  time - Section 5 - Pages 30
10222 487.9 Small omega - Number distinct prime factors of an integer - https://oeis.org/A001221 - is  $O(\log\log N)$  from Hardy
10223 487.10 Big omega - Number prime factors of an integer with multiplicity - https://oeis.org/A001222 - is sum of prime
10224 487.11 Parallel Construction of Segment Trees applied in another setting - [Helmut Alt, Ludmila Scharf] - computing c
10225 487.12 Function plot of Number of PRAM processors -  $N/(\log N)^k$  - For  $k=1$ ,  $N/\log N$  has been plotted in https://sourceforge
10226 487.13 Interval Hash Trees - [T. F. Syeda-Mahmood, P. Raghavan, N. Megiddo] - http://www.almaden.ibm.com/cs/people/st
10227 487.14 Efficient Parallel Algorithms for Geometric Clustering and Partitioning Problems (1994) - [Amitava Datta] - ht
10228 487.15 Parallel computational geometry of rectangles - [Chandran-Kim-Mount] - https://link.springer.com/article/10.10
10229
10230 -----
10231 488. (THEORY) Thermodynamics Gas Diffusion Entropy Model of Information Diffusion in Social Networks and Text Graphs
10232     - related to 384
10233 -----
10234 Second Law of Thermodynamics implies entropy of a closed system always increases. Gas diffusion in a closed chamber c
10235 at random with in the space of the chamber. Gas chamber is a 3-dimensional grid of volume  $N$ . If in initial state, all
10236
10237 References:
10238 -----
10239 488.1 Solomon Asch Conformity Experiments and Herd behaviour - Information Diffusion in Social Media - Section 7.1 -
10240 488.2 Emperor's New Mind - [Roger Penrose] - Inexorable increase in entropy - Page 405
10241
10242 -----
10243 489. (FEATURE-DONE) NeuronRain AsFer-KingCobra MAC Electronic Money - Proof-of-Work and Universally Unique ID Hash in
10244 14 December 2017
10245 -----
10246 (#) Fictitious Message-As-Currency (MAC) in AsFer-KingCobra has been named "Neuro".
10247 (#) This commit implements a non-trivial proof-of-work computation and finds a universally unique hash id for each Ne
10248 which has 2 leading "ff"s - Proof of Work is analogous to reCAPTCHA in websites for filtering out robots
10249 (#) Unique id is created from Boost UUID random generator and checked in a loop for 2 leading "ff" in stringified hex
10250 (#) Protocol Buffer version has been upgraded to 3.5/15 and currency.proto has been recompiled with protoc
10251 (#) asfercloudmoveclient.cpp has been updated to make a choice between std::move() and std::forward() move semantics:
10252     - std::move() just does =operator overload and moves Neuro currency over network
10253     - std::forward() + std::move() first deferences rvalue of && for currency uuid and then does =operator overload
10254 (#) Limitation: Presently there is no documented way to create an rvalue for non-primitive datatypes. For example std
10255 as literal string "xxxxxx".
10256
10257 -----
10258 490. (FEATURE-DONE) AsFer-KingCobra Neuro Electronic Currency - Rvalue NonPrimitive Perfect Forward - 18 December 201
10259 -----
10260 (#) New constructor for cloudmove which takes const char* uuid has been defined. This enables
10261 assigning a string literal rvalue to cloudmove<currency::Currency> objects.
10262
10263

```

```

10264 (#) New move operator= which takes const char* uid has been defined. This internally instantiates
10265 a currency::Currency object
10266 (#) New move operator= which takes cloudmove<T>& lvalue has been defined.
10267 (#) New value and a clause for move semantics, "nonprimitiveforward" has been defined. This clause
10268 does std::forward() of an rvalue cloudmove<currency::Currency> and then invokes std::move() of the currency over netw
10269 (#) This differs from move semantics "std::forward" which is specific to std::string uid only, and thus solves the g
10270 (#) client and server logs for this network move have been committed to testlogs.
10271
10272 -----
10273 491. (THEORY) Generalization of Complementation Undecidability to Rationals(Q) and Reals(R) by H10(Hilbert Tenth Prob
10274 Connection between ZF with Axiom of Choice (ZFC) and Complementation - related to 472 - 28 December 2017, 29 March 26
10275 -----
10276 Thus far Function Complementation described in drafts of this document are oriented towards set of natural numbers or
10277
10278 Axiom of Choice: For set of sets  $S=\{s_1, s_2, s_3, \dots\}$  there exists a choice function  $C(s_i)=x_i$  which chooses an element  $x_i$ 
10279
10280 Following is a special case example of Axiom of Choice in Boolean Social Choice functions:
10281 Depth-2 boolean function/circuit B leaves of which are sets  $s_1, s_2, s_3, \dots$  and nodes at level one are  $C(s_1)=x_1, C(s_2)=x_2$ 
10282
10283 Disjoint Set Cover is also known as Exact Cover defined as subcollection  $S'$  of collection of subsets  $S$  of a universal
10284  $X$  is contained in exactly one subset in  $S'$ .  $S'$  is a disjoint collection and the exact set cover of  $X$ . Exact Cover pr
10285 solved by DLX Dancing Links algorithm. Complementary or Ramsey k-colored sets are created by Exact Set Cover.
10286
10287 References:
10288 -----
10289 491.1 Diophantines for Reals - http://wwwmayr.in.tum.de/konferenzen/Jass07/courses/1/Sadovnikov/Sadovnikov\_Paper.pdf
10290 491.2 Uncountable sets and non-recursively enumerable languages - http://www.cs.colostate.edu/~massey/Teaching/cs301
10291 491.3 Deciding the Undecidable - https://books.google.co.in/books?id=1rjnCwAAQBAJ&pg=PA10&lpg=PA10&dq=real+solutions+
10292 491.4 Introduction to Automata Theory, Languages and Computation - [John E.Hopcroft,Rajeev Motwani,Jeffrey D.Ullman]
10293 491.5 Real Roots of polynomials - https://en.wikipedia.org/wiki/Root-finding\_algorithm
10294 491.6 Constructing Diophantine Representation of a Listable Set, Register Machines preferred over Turing Machines - h
10295 491.7 Diophantine Representation, Non-Deterministic Diophantine Machine (NDDM), Complexity class NP, Single Fold Diop
10296 491.8 DPR theorem and finite-fold diophantine representations - [Yuri Matiyasevich] - ftp://ftp.pdmi.ras.ru/pub/publi
10297 491.9 Factoring Semi-primes (numbers of the form  $N=pq$  for prime  $p,q$ ) by Diophantine Equations - http://www2.mae.ulfr
10298 491.10 Dancing Links X Algorithm For Exact Cover - Pentominoes Example - 4-way doubly linked list - [Donald E. Knuth]
10299 491.11 Dancing Links - [Hitotumatu, Hirosi; Noshita, Kohei] (1979). "A Technique for Implementing Backtrack Algorithm
10300
10301 -----
10302 492. (THEORY and FEATURE-DONE) Complement Function Map Construction - Diophantine Representation - Lagrange's Four Sc
10303 (Draft updates to: https://arxiv.org/abs/1106.4102) - related to 472 - 4 January 2018
10304
10305 (#) This commit implements diophantine representation of an enumerable recursive set by Sum of Four squares solver
10306 in SymPy.
10307 (#) New function that enumerates each element  $x$  of the complement set and applies it as a parameter to Sum of Squares
10308 to obtain the quadruple  $(a,b,c,d)$  such that  $a^2 + b^2 + c^2 + d^2 = x$ 
10309 (#) This is mostly partial recursive function and not necessarily a total recursive function(defined for all possible
10310 (#) logs for this have been committed to testlogs/
10311 (#) SymPy has other diophantine solvers too which require more than one parameters.
10312 (#) SymPy does not have exponential diophantine support yet which if available could construct an exponential diophar
10313 recursively enumerable set ('almost' because of MRDP theorem - there are diophantine equations for recursively enumer
10314
10315 Any partial function  $f:X \rightarrow Y$  which maps a subset  $X'$  of  $X$  to  $Y$ , can be converted to a total function by mapping all el
10316
10317 References:
10318 -----
10319 492.1 Reduction of arbitrary diophantine equation to one in 13 unknowns - [Matijasevic-Robinson] - http://matwbn.icm.
10320 492.2 Distinction between Enumerable and Effectively Enumerable - http://faculty.washington.edu/keyt/Effenumerability
10321     (*) first 13-tuples are found by a diophantine solver and
10322     (*) these tuples are listed as  $t(0), t(1), t(2), \dots$ 
10323 492.3 Function Spaces - Extending partial function to a total function - https://en.wikipedia.org/wiki/Partial\_function
10324
10325 -----
10326 493. (FEATURE-DONE) Computation Geometric Factorization - Binary Search for Tiles - Optimization - Benchmarks - Revis
10327 - related to 481
10328
10329 (#) Factorization benchmarks for Tile binary search optimization have been redone on dual core (local[2]) after remov
10330 (#) Following are the durations for factoring same 24 bit integer factorized previously after removing print statemer
10331
10332 Factorization of 9333123 (24-bit) - without print statements
10333 -----
10334 real 35m56.196s (Spark Duration = 1839.146seconds)
10335 user 3m2.836s
10336 sys 4m56.668s
10337
10338 Factorization of 9333123 (24-bit) - with print statements earlier
10339 -----
10340 real 112m24.101s (Spark duration 12:21 to 14:02 = 101minutes = 6060seconds)
10341 user 0m0.000s
10342 sys 0m0.004s
10343 =====
10344 Factors of 9333123 are (excerpt from logs):

```

```

10345 =====
10346 ...
10347 Factor is = 219
10348 Factor is = 1387
10349 Factor is = 2243
10350 Factor is = 4161
10351 Factor is = 6729
10352 Factor is = 6729
10353 Factor is = 42617
10354 Factor is = 127851
10355 Factor is = 163739
10356 Factor is = 491217
10357 Factor is = 3111041
10358 Factor is = 9333123
10359 =====
10360 (#) Compressed Spark log for this factorization has been committed to python-src/testlogs/
10361 (#) General Number Field Sieve algorithm is sequential, exponential in number of bits and requires  $O(2^{(c(\log N)^0.33})$ 
10362
10363
10364 494. (THEORY and FEATURE-DONE) Complement Diophantine Map - Converts a Partial Function to Total Function - 6 January
10365 -----
10366 (#) Sum of Four Squares diophantine solutions are quadruples  $(a,b,c,d)$  which form a subset of all possible tuples and
10367 complement function unknowns-to-parameter map is partial.
10368 (#) This is remedied by extending the parameter codomain by adding -1 as additional possible parameter value and map.
10369 (#) logs for this have been committed to testlogs/
10370
10371
10372 495. (THEORY) Factoring as a service - General Number Field Sieve on Amazon EC2 cloud - RSA 512 bit - Relevance to Cc
10373 Geometric NC-PRAM-Multicore Factorization Theoretical  $O((\log N)^2)$  bound - related to 482 - 9 January 2018
10374 -----
10375 Number field sieve has been implemented as Amazon EC2 cloud service. Benchmarks for RSA 512 bit achieve factorization
10376 4 hours applying CADO-NFS and MSieve NFS implementations optimized for Elastic Cloud. Instance type used is c4.8xlarge
10377
10378 References:
10379 -----
10380 495.1 Factoring as a service - slides - http://crypto.2013.rump.cr.yp.to/981774ce07e51813fd4466612a78601b.pdf
10381 495.2 Factoring as a service - https://github.com/eniac/faas - Parallelizing Number Field Sieve - Polynomial selectic
10382
10383 -----
10384 496. (THEORY and FEATURE-DONE) Computational Geometric Factorization Update - Local Tile Computation and necessity fc
10385 10 January 2018 - 30-bit integer dual core single node Spark Cluster benchmark - related to 495
10386
10387 As mentioned in previous section, reading tiles from storage in SparkContext.parallelize() is a serious bottleneck. I
10388
10389 Factorization of 921234437:
10390 -----
10391 18/01/10 17:56:56 INFO Utils: /home/shrinivaasanka/Krishna_iResearch_OpenSource/GitHub/asfer-github-code/python-src/C
10392 Factor is = 1
10393 Factor is = 17
10394 Factor is = 19
10395 Factor is = 59
10396 Factor is = 323
10397 Factor is = 1003
10398 Factor is = 1121
10399 Factor is = 19057
10400 Factor is = 48341
10401 Factor is = 821797
10402 Factor is = 918479
10403 Factor is = 2852119
10404 Factor is = 15614143
10405 Factor is = 48486023
10406 Factor is = 54190261
10407 18/01/10 18:08:51 INFO PythonRunner: Times: total = 714516, boot = 649, init = 23, finish = 713844
10408
10409 Spark Duration: 18:08:51 - 17:56:56 = 535seconds
10410
10411 Spark-Python has RPC and serialization latencies and following numbers could be better if implemented in a different
10412
10413 -----
10414 497. (THEORY and FEATURE-DONE) Computational Geometric Factorization - Non-Persistent Tile Segments - 30 bit Single N
10415 -----
10416 (#) Benchmarks for factoring another 30-bit integer 999994437 on single node dual core Spark cluster have been commit
10417 (#) Similar to previous 30 bit integer, time utility prints 40 minutes 56 seconds while the actual Spark duration is
10418 18/01/11 13:34:34 INFO Utils: /home/shrinivaasanka/Krishna_iResearch_OpenSource/GitHub/asfer-github-code/python-src/C
10419 =====
10420 Factor is = 1
10421 =====
10422 =====
10423 Factor is = 3
10424 =====
10425 =====

```

```
10426 Factor is = 9
10427 =====
10428 =====
10429 Factor is = 13
10430 =====
10431 =====
10432 Factor is = 23
10433 =====
10434 =====
10435 Factor is = 27
10436 =====
10437 =====
10438 Factor is = 39
10439 =====
10440 =====
10441 Factor is = 69
10442 =====
10443 =====
10444 Factor is = 97
10445 =====
10446 =====
10447 Factor is = 117
10448 =====
10449 =====
10450 Factor is = 207
10451 =====
10452 =====
10453 Factor is = 291
10454 =====
10455 =====
10456 Factor is = 299
10457 =====
10458 =====
10459 Factor is = 351
10460 =====
10461 =====
10462 Factor is = 621
10463 =====
10464 =====
10465 Factor is = 873
10466 =====
10467 =====
10468 Factor is = 897
10469 =====
10470 =====
10471 Factor is = 1261
10472 =====
10473 =====
10474 Factor is = 1277
10475 =====
10476 =====
10477 Factor is = 2231
10478 =====
10479 =====
10480 Factor is = 2619
10481 =====
10482 =====
10483 Factor is = 2691
10484 =====
10485 =====
10486 Factor is = 3783
10487 =====
10488 =====
10489 Factor is = 3831
10490 =====
10491 =====
10492 Factor is = 6693
10493 =====
10494 =====
10495 Factor is = 8073
10496 =====
10497 =====
10498 Factor is = 11349
10499 =====
10500 =====
10501 Factor is = 11493
10502 =====
10503 =====
10504 Factor is = 16601
10505 =====
10506 =====
```

```
10507 Factor is = 20079
10508 =====
10509 =====
10510 Factor is = 29003
10511 =====
10512 =====
10513 Factor is = 29371
10514 =====
10515 =====
10516 Factor is = 34047
10517 =====
10518 =====
10519 Factor is = 34479
10520 =====
10521 =====
10522 Factor is = 49803
10523 =====
10524 =====
10525 Factor is = 60237
10526 =====
10527 =====
10528 Factor is = 87009
10529 =====
10530 =====
10531 Factor is = 88113
10532 =====
10533 =====
10534 Factor is = 123869
10535 =====
10536 =====
10537 Factor is = 149409
10538 =====
10539 =====
10540 Factor is = 261027
10541 =====
10542 =====
10543 Factor is = 264339
10544 =====
10545 =====
10546 Factor is = 371607
10547 =====
10548 =====
10549 Factor is = 381823
10550 =====
10551 =====
10552 Factor is = 448227
10553 =====
10554 =====
10555 Factor is = 783081
10556 =====
10557 =====
10558 Factor is = 793017
10559 =====
10560 =====
10561 Factor is = 1114821
10562 =====
10563 =====
10564 Factor is = 1145469
10565 =====
10566 =====
10567 Factor is = 1610297
10568 =====
10569 =====
10570 Factor is = 2848987
10571 =====
10572 =====
10573 Factor is = 3344463
10574 =====
10575 =====
10576 Factor is = 3436407
10577 =====
10578 =====
10579 Factor is = 4830891
10580 =====
10581 =====
10582 Factor is = 8546961
10583 =====
10584 =====
10585 Factor is = 10309221
10586 =====
10587 =====
```

```

10588 Factor is = 14492673
10589 =====
10590 =====
10591 Factor is = 25640883
10592 =====
10593 =====
10594 Factor is = 37036831
10595 =====
10596 =====
10597 Factor is = 43478019
10598 =====
10599 =====
10600 Factor is = 76922649
10601 =====
10602 =====
10603 Factor is = 111110493
10604 =====
10605 18/01/11 13:48:32 INFO PythonRunner: Times: total = 837634, boot = 641, init = 37, finish = 836956
10606 18/01/11 13:48:32 INFO Executor: Finished task 0.0 in stage 0.0 (TID 0). 1529 bytes result sent to driver
10607 18/01/11 13:48:32 INFO TaskSetManager: Starting task 1.0 in stage 0.0 (TID 1, localhost, executor driver, partition 1
10608 18/01/11 13:48:32 INFO Executor: Running task 1.0 in stage 0.0 (TID 1)
10609 =====
10610 Factor is = 333331479
10611 =====
10612 18/01/11 13:48:32 INFO TaskSetManager: Finished task 0.0 in stage 0.0 (TID 0) in 838426 ms on localhost (executor dri
10613 which is almost 14 minutes ( 13:48:32 - 13:34:34 ). First non-trivial factor was printed within 10 seconds. Time util
10615 -----
10616 498. (THEORY and FEATURE-DONE) Computational Geometric Factorization - Non-Persistent Tile Segments - 31 bit Single M
10617 -----
10618 31-bit integer 2147483647 has been factorized by searching non-persisted pixelated hyperbolic tile segments. Only tri
10619 -----
10620 -----
10621 Factorization/Primality of 2147483647
10622 -----
10623 18/01/12 14:33:12 INFO Utils: /home/shrinivaasanka/Krishna_iResearch_OpenSource/GitHub/asfer-github-code/python-src/|
10624 -----
10625 Factor is = 1
10626 -----
10627 18/01/12 15:02:57 INFO PythonRunner: Times: total = 1784724, boot = 643, init = 23, finish = 1784058
10628 -----
10629 Spark Duration 15:02:57 - 14:33:12 = 29 minutes 45 seconds
10630 -----
10631 Spark Logs have been committed to python-src/testlogs/
10632 -----
10633 -----
10634 References:
10635 -----
10636 498.1 Multiplicative Partition Function - ON THE OPPENHEIM000 000 FACTORISATIO NUMERORUM000 FUNCTION - [FLORIAN LUCA,
10637 498.2 Multiplicative Partition Function - https://oeis.org/A001055
10638 498.3 Bound for Multiplicative Partition Function - [Canfield-Erdos-Pomerance] - https://www.math.dartmouth.edu/~carl
10639 498.4 Eighth Mersenne Prime -  $2^{31} - 1 = 2147483647$  - https://en.wikipedia.org/wiki/2,147,483,647 - this was largest k
10640 498.5 M31 - http://primes.utm.edu/curios/page.php/2147483647.html - The first prime that cannot be tested on 32-bit p
10641 498.6 Cryptography in NCO - [Benny Applebaum, Yuval Ishai, Eyal Kushilevitz] - http://www.cs.technion.ac.il/~abenny/
10642 498.7 Binary Quadratic Diophantine Equations (BQDE) and BQDE for Factorization - [JC Lagarias] - https://arxiv.org/pc
10643 498.8 Polynomial Time Quantum Algorithm for Solving Pell's Equation - [Hallgren] - http://www.cse.psu.edu/~sjh26/pell
10644 (x+1)/y = a
10645 (x-1)/y = b
10646 2/y = a-b for factors a,b of N.
10647 y = 2/a-b
10648 => (x+1) = 2a/(a-b)
10649 => x = 2a/(a-b) - 1
10650 Historicity of this problem (Brahmagupta's Chakravala) and a polylog approximation based on Newton-Raphson square roo
10651 -----
10652 -----
10653 499. (FEATURE-DONE) Secure Neuro Currency Cloud Perfect Forward Move - OpenSSL client and server - 19 January 2018
10654 -----
10655 Neuro Currency Cloud Perfect Forward Move socket code has been openSSL enabled:
10656 - Makefile updated include -DOPENSSL #ifdef option for compiling SSL client-server headers
10657 - license headers updated
10658 - new header asfercloudmove_openssl.h has been added to repository for invoking openSSL client and server functions i
10659 and opensslserver.h
10660 - An example fictitious X.509 cert.pem and key.pem have been created by openssl utility for certificate verification
10661 - new headers opensslclient.h and opensslserver.h have been added to repository which define openSSL client and serve
10662 are reference examples in www.openssl.org Wiki changed for cloud move)
10663 - logs for SSL cloud_move client and server have been committed to cloud_move/testlogs/
10664 -----
10665 -----
10666 500. (FEATURE-DONE) Searching Unsorted List of Numbers - Algorithm in GRAFIT Open Learning Implemented - 21 January 2
10667 -----
10668 An algorithm to search list of numbers better than bruteforce search mentioned in GRAFIT Course Notes:

```

10669 https://github.com/shrinivaasanka/Grafit/blob/master/course_material/ComputerScienceMiscellaneous/ComputerScienceMisc
10670 has been implemented in NeuronRain AsFer.

10671 This lifts one dimensional numbers to multidimensional tuples and creates hashtables for each dimension of tuple. Loc
10672 lookup of each digit in query in these hash tables in succession. If all hash lookups succeed queried number exists i
10673
10674 This implementation pads each number with "#" so that it is right justified and maximum number of digits is stipulate
10675
10676
10677 Searching Unsorted lists is the most fundamental open research problem and this implementation uses Locality sensitiv
10678 . Python dictionaries are hash maps and not hash tables which support collisions. Each digit in query is lookedup for
10679 there is a match digitmatch is set to True. Logical AND of all digit matches is returned as True/False.

10680
10681
10682 501. (THEORY) Answer-Questioning (Reversal of Interview) and Recursive Gloss Overlap Dense Subgraph Classification -
10683 - related to 413, 421

10684
10685 Recursive Gloss Overlap Definition Graph of a text previously has been demonstrated to classify documents in unsuperv
10686 dense subgraphs: centrality, k-cores, pageranks etc., Dense subgraphs of text graph extract the essence of an article
10687 which may or may not be present in the document. Keywords not present in the document can be classes of a document be
10688 deep learning of definitions. From the keywords, a question or set of permutations of questions can be constructed wh
10689 Relevance of Question depends on the relatedness e.g Tensor Neuron of all possible pairs of keyword class vertices.

10690
10691 Example:
10692
10693 If a text graph of an academic research text has been classified in following word vertices of high core numbers
10694 [Prime, Factorization, Theorem, Composites, Diophantine, Polynomials,...]
10695 in decreasing value of centrality/k-core/pagerank and pairwise Tensor Neuron potentials are ranked as below:
10696 Prime-Factorization = 0.34234
10697 Theorem-Composites=0.33333
10698 Diophantine-polynomials=0.221212
10699 ... and so on
10700 then question(s) can be constructed based on previous ranking of Tensor relatedness as:
10701 Does this article discuss relation between [Primes] and [Factorization]?
10702

10703
10704 Reference:
10705
10706 501.1 CALO, SIRI, PAL - <https://pal.sri.com/architecture/> - Cognitive Assistants, Question Answering

10707
10708
10709 502. (FEATURE-DONE) Scheduler Analytics - Interprocess Distance Computation by DictDiffer - 24 January 2018

10710
10711 1. Representing OS Process Information as Feature Vectors has been mentioned as Software Scheduler Analytics usecase
10712 <http://neuronrain-documentation.readthedocs.io/en/latest/>
10713 2. This commit implements a new python function which reads process info as a dictionary from psutils. Psutils has an
10714 process metrics or to read the dictionary in its entirety.
10715 3. Psutils per-process dictionary has all the basic details pertaining to instantaneous resource consumptions of a pr
10716 4. These per-process features are collated in an array and are json.dump()-ed as strings in asfer.enterprise.encstr.s
10717 which can be used as input by clustering/classification NeuronRain-AsFer C++ implementations.
10718 5. logs for this have been committed to software_analytics/testlogs/DeepLearning_SchedulerAnalytics.log.24January2018
10719 6. Distance between two process feature dictionaries/vectors are printed by DictDiffer which has been imported and le
10720 the distance function between any two processes.

10721
10722
10723 503. (FEATURE-DONE) Ephemeris Search - Maitreya Text Client version 8.0 - 25 January 2018
10724 (Only in NeuronRain Research - SourceForge)

10725
10726 1. python-src/MaitreyaEncHoro_RuleSearch.py has been updated to invoke Maitreya Text Client 8.0 and an option to choc
10727 Maitreya text client 7.0 and 8.0.
10728 2. geonames import has been made optional - only if useGeoNames is True
10729 3. Example rule search logs by maitreya 8.0 text client - chartsummary.rulesearch and python-src/testlogs/MaitreyaEnc

10730
10731
10732 504. (FEATURE-DONE) Streaming Algorithms - Encoded Strings Data Source - 26 January 2018
10733 (For Astronomical Encoded Strings)

10734
10735 1. python-src/Streaming_AbstractGenerator.py iterator has been updated for new data storage "AsFer_Encoded_Strings" a
10736 for streaming encoded strings created by NeuronRain AsFer
10737 2. Streaming algorithm implementations have been updated to stream data from this new datasource and logs have been c

10738
10739
10740 505. (THEORY) Computational Geometric Factorization - Feasibility of Sequential Optimization - related to 487 - 6 Feb

10741
10742 Doing away with Parallel RAMs in Computational Geometric Factorization by breaking the hyperbolic arc bow into two se
10743 and searching their concatenations which are implicitly sorted ascending, has problems because concatenation of multi
10744 in O(logN) time by using Rope Strings which are tree representations of strings (logarithmic in length of strings and
10745 strings). But concatenation of multiple strings/tiles logarithmic time in number of strings is still open.

10746
10747 Following sequential optimization tries to find feasibility of doing Sequential Factorization without PRAMs and conca
10748 number_to_factorize=N

```

10750 factor_candidate=N/2
10751
10752 -----
10753 Loop for subsegment1 tree:
10754 -----
10755 while(factor is not found)
10756 {
10757     1. Find the tile segment/interval containing factor candidate.
10758     [2. Split the candidate tile segment to two subsegments - subsegment1 contains points which are less than prev
10759     3. Binary Search each node in subsegment1 tree for factor points (p,q) (N=pq) - There are 3 possibilities:
10760     3.1 All points in this subsegment1 tree node are less than N => Binary Search has to be done on right subsegme
10761     3.2 All points in this subsegment1 tree node are greater than N => Search has to be done on left subsegment1 s
10762     3.3 N is present in this subsegment1 tree node and factor point N=pq is found
10763 }
10764
10765 -----
10766 Loop for subsegment2 tree:
10767 -----
10768 while(factor is not found)
10769 {
10770     4. Find the tile segment/interval containing factor candidate.
10771     [5. Split the candidate tile segment to two subsegments - subsegment1 contains points which are less than prev
10772     6. Binary Search each node in subsegment2 tree for factor points (p,q) (N=pq) - There are 3 possibilities:
10773     6.1 All points in this subsegment2 tree node are less than N => Binary Search has to be done on right subsegme
10774     6.2 All points in this subsegment2 tree node are greater than N => Search has to be done on left subsegment2 s
10775     6.3 N is present in this subsegment2 tree node and factor point N=pq is found
10776 }
10777
10778 7.Above algorithm is Depth-2 Two Level Binary Search:
10779 7.1) First binary search finds the subsegment node in subsegment trees in O(logN)
10780 7.2) Second binary search searches within subsegment node in O(logN)
10781 and thus requires O(logN*logN) sequential time.
10782
10783 8. Sets of subsegment1(s) and subsegment2(s) constitute 2 binary search trees of segments, but these two search trees
10784
10785 9. Finding tile segment containing a factor candidate point is non-trivial planar point location problem in general.
10786 Sum of lengths of k consecutive hyperbolic pixelated tiles = N/(1*2) + N/(2*3) + N/(3*4) + ... + N/(k*(k+1))
10787     = N(1/1 - 1/2 + 1/2 - 1/3 + 1/3 - 1/4 + ... + 1/k - 1/(k+1))
10788     = N(1 - 1/(k+1))
10789     = Nk/(k+1)
10790 Tile containing point x:
10791     Nk/(k+1) < x < N(k+1)/(k+2)
10792     k < x/(N-x)
10793 integer round-off of k is the index of tile interval containing x.
10794
10795 10. Previous sequential optimization of O((logN)^2) though removes PRAMs, proves only that Factorization is in P. Com
10796
10797 11. For each segment k in loops previously, 2 subsegments of it have following interval endpoints - (xleft,yleft,xrig
10798     subsegment1: (N/(k+2),(k+1),N/(k+2)+delta,(k+1))
10799     subsegment2: (N/(k+2)+delta,(k+1),N/(k+1),(k+1))
10800 and delta=N/((k+1)(k+2))
10801
10802
10803 506. (THEORY) Tournament Graph Election, Coloring, Intrinsic Merit, Partitions and Bell Number - 8 February 2018
10804 -----
10805 Tournament Graph of n vertices has n(n-1)/2 edges (complete). Each vertex of the tournament graph is uniquely colored
10806 Each edge (v1,v2) is the contest between vertices v1 and v2. Each edge of the tournament graph is progressively color
10807 all possible partitions of a set is the Bell number. Vertex corresponding to Color of the biggest part in this edge s
10808
10809
10810 507. (FEATURE-DONE) Streaming Analytics Abstract Generator Update - Socket Streaming Datasource Added - 8 February 20
10811 -----
10812 1.Streaming Abstract Generator facade/generator pattern implementation has been updated for a new "Socket Streaming"
10813 2.Constructor Datasource arg is the remote host and port is hardcoded to 64001 (one more than kernel_analytics driver
10814 3.Python socket has been imported and socket client code has been added to __iter__()
10815 4.As example, Hyper LogLog Counter Streaming implementation has been updated to read streaming data from remote strea
10816 5.Logs for this have been committed to testlogs/
10817 6.Example webserver commandline:
10818     nc -l 64001
10819     ><data>
10820
10821 -----
10822 508. (FEATURE-DONE) Scheduler Analytics - Socket Streaming Server - Decorator pattern implementation - 9 February 201
10823 -----
10824 1. New Socket Streaming Server for Scheduler Analytics has been implemented in python-src/software_analytics/Schedule
10825 2. This invokes get_stream_data() function in python-src/software_analytics/DeepLearning_SchedulerAnalytics.py
10826 3. get_stream_data() function is decorated by a Decorator class implemented in a new file python-src/webserver_rest_u
10827 4. SocketWebServerDecorator implemented in python-src/webserver_rest_ui/NeuronRain_Generic_WebServer.py is generic ar
10828     __init__() and __call__() functions. __call__() invokes the decoratee function get_stream_data() specific to Schedul
10829 5. SocketWebServerDecorator can decorate any other streaming datasource, not just scheduler analytics - decoratee fur
10830 6. Logs for Socket Streaming Server have been committed to python-src/software_analytics/testlogs/SchedulerAnalytics_

```

10831 7. Global configs for socket streaming server host and port (64001) have been set in a new config file python-src/sof
 10832 8. Known issue: There seems to be a random iterator disconnect because of psutil process_iter() process statistics st
 10833
 10834 -----
 10835 509. (FEATURE-DONE) Scheduler Analytics Socket Streaming Decorator - Psutil iterator frequent disconnects resolution
 10836 -----
 10837 1. SocketWebServerDecorator frequently and periodically throws "NoneType object not callable" exception.
 10838 2. This exception happens after every 215 or 217 processes (not sure what this magic number is)
 10839 3. Because of this try/except error handling has been added throughout decorator code
 10840 4. Socket listen queue size has been increased to 100
 10841 5. datasourcefunc() is re-called once an exception is thrown in a loop - a palliative cure
 10842 6. After this 215 barrier is breached. Logs for 558 processes streamed by Socket Server Decorator and received by Str
 10843 Generator client have been committed to python-src/software_analytics/testlogs/SchedulerAnalytics_WebServer.log.11Feb
 10844 python-src/testlogs/Streaming_HyperLogLogCounter.log.11February2018
 10845
 10846 -----
 10847 510. (FEATURE-DONE) Approximate 3SAT Solver Randomized Rounding Update - NumPy random choice() replacing permutation()
 10848 -----
 10849 1. CNFSATSolver.py - function creating random 3SAT instances has been updated to invoke NumPy random choice() instead
 10850 permutation() without replacement - equivalent to np3 per clause for n variables.
 10851 2. Logs for 16 variables - 16 clauses and 18 variables - 18 clauses have been committed to testlogs/CNFSATSolver.16va
 10852 and testlogs/CNFSATSolver.18variables18clauses.log.27February2018
 10853 3. Numpy random choice() is based on Uniform distribution.
 10854 4. It is remarkable to note that observed probability average and Random Matrix probability $1/\sqrt{m \cdot n}$
 10855 are strikingly equal - a confirmation of the least squares randomized rounding and relaxation SAT solver's accuracy
 10856 5. Logs for 16*16 and 18*18 have few hundreds and thousand plus random 3SAT instances which are solved 100%
 10857
 10858 -----
 10859 511. (FEATURE-DONE) ConceptNet5 Update - REST endpoints changed - 27 February 2018
 10860 -----
 10861 1. ConceptNet5 rest_client.py has been imported which already wraps REST methods and endpoints
 10862 2. REST endpoints for search,lookup and query have been updated for ConceptNet 5.5 which were 5.4 earlier
 10863
 10864 -----
 10865 512. (FEATURE-DONE and THEORY) Approximate SAT Solver and ConceptNet REST client updates - 21 variables,21 clauses LS
 10866 -----
 10867 1.Least Square SAT solver has been updated to print more readable debug messages and highlight MAXSAT approximation r
 10868 average for SATs solved thus far
 10869 2.Number of variables and clauses is set to 21,21 and MAXSAT ratio is 98% for 34 random 3SATs
 10870 3.Logs for 21,21 has been committed to testlogs/CNFSATSolver.21variables21clauses.log.28February2018 which shows the
 10871 probabilities and random matrix $1/\sqrt{m \cdot n}$ literal probability agreeing well.
 10872 4.This is because of uniform unbiased (mostly) choice() when number of clauses = number of variables causing $1/\sqrt{m \cdot n}$
 10873 5.For unequal clauses and variables numbers, an epsilon biased PRG implementation in linux kernel is necessary (randc
 10874 rewritten)
 10875 -----
 10876 6.ConceptNet5 client has been updated to include a related() function wrapper which invokes /related REST endpoint fc
 10877 7.ConceptNet5 finds related concepts by word embeddings implementation of word2vec which maps each word to a vector a
 10878 are clustered together in this vector space. More precisely, word distances are represented as a word-word 2 dimensic
 10879 and sum of path edge weights between word pair is the distance.
 10880 8.For finding distance between two concepts a common ancestor algorithm has been implemented in new conceptnet_dstar
 10881 9.Common ancestors are printed in end and distance between the concepts is also printed
 10882 10.Some example conceptnet_distance() invocations have been captured in ConceptNet/testlogs/ConceptNet5Client.log.28F
 10883
 10884 References:
 10885 -----
 10886 512.1 ConceptNet 5.5: An Open Multilingual Graph of General Knowledge - [Robert Speer,Joshua Chin,Catherine Havasi-Lu
 10887 512.2 ConceptNet blog - <https://blog.conceptnet.io/>
 10888 512.3 Microsoft Concept Graph - Probable - <https://concept.research.microsoft.com/Home/Introduction> - similar to Conce
 10889
 10890 -----
 10891 513. (THEORY) ConceptNet, Graph Tensor Neuron Network Intrinsic Merit, Word2Vec Word Embeddings - 2 March 2018 - rela
 10892 -----
 10893 ConceptNet5 /related REST endpoint retrieves concepts similar to a concept and ranks them by word2vec word embedding
 10894 e Lambda Function Growth algorithm mentioned previously, grows lambda functions for random walks in a text definiti
 10895 e Gloss Overlap and word-word similarity/relevance is formalized by Neural Tensor Network. ConceptNet /related word2v
 10896
 10897 Rationale for creating random walks in text definition graph is: Process of Human Text Comprehension is simulated by
 10898
 10899 References:
 10900 -----
 10901 513.1 Neural Tensor Network - [Socher-Chen-Manning-Ng] - https://nlp.stanford.edu/pubs/SocherChenManningNg_NIPS2013.pdf
 10902 513.2 The Language Instinct - [Steven Pinker] - Chapter 4 - How Language Works - Word Chains and Chomsky
 10903 513.3 Chomsky-Norvig Debate on Algorithmic Versus Statistical Learning - <http://daselab.cs.wright.edu/nesy/NeSy13/noi>
 10904 <quote>
 10905 - Statistical language models have had engineering success, but that is irrelevant to science.
 10906 - Accurately modeling linguistic facts is just butterfly collecting; what matters in science (and specifically
 10907 - Statistical models are incomprehensible; they provide no insight.
 10908 - Statistical models may provide an accurate simulation of some phenomena, but the simulation is done complet
 10909 - Statistical models have been proven incapable of learning language; therefore language must be innate, so w
 10910 <unquote>
 10911 Recursive Gloss Overlap and Recursive Lambda Function Growth are Algorithmic Language Learning Models.

10912 513.4 Gold's Theorem - www.lps.uci.edu/~johnsonk/Publications/Johnson.GoldsTheorem.pdf and limit on learnability - 1
 10913
 10914
 10915 514. (THEORY and FEATURE-DONE) Recursive Lambda Function Growth - ConceptNet5 support, Per random walk
 10916 Lambda Function Composition Tree Graph Tensor Neuron Network Intrinsic Merit - 3 March 2018 - related to 515
 10917
 10918 Recursive Lambda Function Growth implementation has been updated to print per random walk lambda function
 10919 composition tree and its Graph Tensor Neuron Network Intrinsic Merit. Similarity has been made configurable by a flag
 10920 ...
 10921 grow_lambda_function3(): Maximum Per Random Walk Graph Tensor Neuron Network Intrinsic Merit : (u'(present/etc,(infra
 10922 ...
 10923 ======
 10924 Unsupervised Classification based on top percentile Core numbers of the definition graph(subgraph of WordNet)
 10925 ======
 10926 This document belongs to class: Mumbai ,core number= 12
 10927 This document belongs to class: infrastructure ,core number= 9
 10928 ...
 10929 which is an evidence to the fact intrinsic merit peaks for random walks through high core numbered hub word vertices.
 10930
 10931 References:
 10932 -----
 10933 514.1 Cliques and Cavities in Human Brain - [Ann Sizemore, Chad Giusti, Ari Kahn, Richard F. Betzel, Danielle S. Bass
 10934 514.2 Algebraic topology and Computational Neuroscience - <https://www.technologyreview.com/s/602234/how-the-mathematics-of-topology-is-transforming-neuroscience/>
 10935
 10936 515. (FEATURE-DONE) SAT Solver - verbose print and iterations reduced - 4 March 2018
 10937
 10938 Least Squares LSMR SAT solver implementation has been updated to print LSMR internal calculations. Maximum iterations
 10939
 10940
 10941 516. (THEORY) Majority+Voter Composition Hardness Amplification Lemma, Sensitivity Conjecture - Updated Hardness Bound
 10942 - related to 318,356 - 5 March 2018
 10943
 10944 Hardness Amplification for Majority+Voter Composition has been described earlier by adapting XOR Lemma to Majority fu
 10945
 10946 Hardness of Maj+voter composition [c/sqrt(n*delta)] + [sum(column2 error entries)] - [sum(column3 no error
 10947 entries)] = -----
 10948 Hardness of voter function delta
 10949
 10950 which is based on the subdivided BP* error scenarios matrix mentioned earlier and described again below:
 10951
 10952
 10953 x | f(x) = f(x/e) | f(x) != f(x/e) Noise |
 10954 -----
 10955 x in L, x/e in L | No error | Error |
 10956 -----
 10957 x in L, x/e not in L | Error | No error if f(x)=1,f(x/e)=0 |
 10958 | | else Error |
 10959 -----
 10960 x not in L, x/e in L | Error | No error if f(x)=0,f(x/e)=1 |
 10961 | | else Error |
 10962 -----
 10963 x not in L, x/e not in L | No error | Error |
 10964 -----
 10965
 10966 x | f(x) |
 10967 -----
 10968 Randomized Decision tree evaluation | No error | Error |
 10969 -----
 10970 This matrix picturises the various false positives and false negative errors possible in majority voting. Language L
 10971
 10972 Hardness of Maj+voter composition [sum(column2 entries)] + [sum(column3 entries)] - [sum(all no error entries)]
 10973 ----- = -----
 10974 Hardness of voter function delta
 10975
 10976 But Stability(f(x)) = Pr(f(x)=f(x/e)) - Pr(f(x) != f(x/e)) from definition of Noise stability => Pr(f(x)=f(y)) = (1+
 10977 Sum(column2 entries) = Pr(f(x)=f(y)) = (1+Stability)/2.
 10978 Sum(column3 entries) = NoiseSensitivity
 10979 => Hardness of Maj+Voter composition = (1+Stability)/2 + NoiseSensitivity - [sum(all no error entries)]
 10980 For majority function, Stability = (2/pi)*delta + 0((delta)^1.5) and NoiseSensitivity = 0(1/sqrt(n*delta))
 10981 => Hardness of Maj+Voter composition = 1 + (2/pi)*delta + 0((delta)^1.5) + 0(1/sqrt(n*delta)) - [sum(all no error ent
 10982 For large n, previous hardness tends to 1 + (2/pi)*delta + 0((delta)^1.5) - [sum(all no error entries)]
 10983
 10984 From definition of BP*, Probability of No error entries >= 2/3 => Sum(all no error entries) >= 2/3
 10985 => Hardness of Maj+Voter composition <= [pi + 2*delta + k*pi*(delta)^1.5]/2*pi - 2/3
 10986 => Hardness Amplification for Majority+Voter Composition <= [3*pi + 6*delta + 6k*pi*(delta)^1.5 - 2] /[6*pi*delta]
 10987 -----
 10988 => Hardness Amplification for Majority+Voter Composition <= 1/delta*(1/2-1/3*pi) + 1/pi + 6k*pi*(delta)^0.5
 10989 -----
 10990 which is huge amplification for small hardness of voter boolean functions.
 10991 => weak voters are hardened by majority
 10992 => Computing majority by a circuit is increasingly hard as voters become weak (intuitively obvious because if voters

```

10993 Sensitivity Conjecture polynomially relates sensitivity and block sensitivity of boolean functions as: s(f) <= bs(f)
10994 for_all_length_e(Number of correlations x/e for which [f(x) != f(x/e)])
10995 -----
10996 for_all_length_e(Number of correlations x/e for which [f(x) == f(x/e)] + Number of correlations x/e for which
10997
10998 Sensitivity and Block Sensitivity are maximum values of e(which can be number of bits or number of blocks) in summati
11000
11001 NOTE: Here hardness of voter boolean function is approximately assumed to equal NoiseSensitivity of Voter Boolean Fur
11002 -----
11003 => Hardness Amplification for Majority+Voter Composition <= 1/(delta + or - error)*(1/2-1/3*pi) + 1/pi + 6k*pi*(delta
11004 -----
11005
11006
11007 517. (THEORY and FEATURE-DONE) Hardness of Majority Voting, SAT Solver Update - Compressed Sensing and Moore-Penrose
11008 - Conflicts - 6 March 2018 - related to 516
11009 -----
11010 Approximate CNF SAT Solver has been updated to invoke Moore-Penrose Pseudoinverse function to compute approximate inv
11011 (#) Hardness of Majority+Voter Boolean Function Composition in both directions - bottom-up Voter-Majority and
11012 (#) SAT Solver random matrix analysis per-literal probability agrees with observed findings so far in small nu
11013 (#) If Hardness of Majority implies something stronger than P != NP e.g an one-way function or PRG in #P^#P th
11014
11015
11016 518. (THEORY and FEATURE-DONE) SAT Solver Update - pinv2() - 1000 variables and 1000 clauses - 6 March 2018 - related
11017 -----
11018 SAT Solver has been updated to use pinv2() pseudoinverse function which has been documented to be faster. After remov
11019 redundant bottleneck, 1000 variables-1000 clauses random SATs have been solved by pinv2() and matrix multiplication t
11020
11021
11022 519. (THEORY and FEATURE-DONE) SAT Solver Update - 2500 clauses and 2500 variables - LSMR,LSQR and PseudoInverse Benc
11023 - 9 March 2018
11024 -----
11025 1. SAT Solver class has been changed to accept the algorithm as parameter which can be function names for LSMR,LSQR,F
11026 SOLVE etc.,
11027 2. 2500 variables and 2500 clauses combination of SAT instances have been benchmarked by invoking LSMR, LSQR and Pseu
11028 3. LSMR benchmark has 405 random 3SAT instances and is the fastest, LSQR and PseudoInverse(pinv2) benchmarks have onl
11029 4. LSQR and PseudoInverse(pinv2) are equally slower compared to LSMR by many orders of magnitude.
11030 5. But approximation ratio for LSMR is 91-92% while LSQR and PseudoInverse trend at 96-97% though for small number of
11031 implies an accuracy versus speed tradeoff: LSMR is less accurate but fast while LSQR and PseudoInverse(pinv2) are mor
11032 6. Observed probability per literal for all three coincide with random matrix 1/sqrt(m*n) uniform distribution probab
11033 7. These numbers are only representative figures and number of iterations for LSQR and PseudoInverse(pinv2) are too n
11034 8. Logs have been committed to:
11035     python-src/testlogs/CNFSATSolver.2500clauses2500variables.LSMR.log.9March2018
11036     python-src/testlogs/CNFSATSolver.2500clauses2500variables.LSQR.log.9March2018
11037     python-src/testlogs/CNFSATSolver.2500clauses2500variables.PseudoInverse.log.9March2018
11038
11039
11040 520. (THEORY and FEATURE-DONE) SAT Solver Update - Non-Uniform Choice - For both equal and unequal number of clauses
11041 related to 519 - 11 March 2018
11042 -----
11043 SAT Solver has been updated to include a new Non-Uniform Choice function for creating random SAT instances by choosir
11044 probability = 1/sqrt(m*n) which works for both equal and unequal number of clauses. This new function chooses non-uni
11045 1000 variables, 1000 clauses - CNFSATSolver.1000variables1000clauses.NonUniformChoice.log.11March2018
11046 1100 variables, 1200 clauses - CNFSATSolver.1100variables1200clauses.NonUniformChoice.log.11March2018
11047 1200 variables, 1100 clauses - CNFSATSolver.1200variables1100clauses.NonUniformChoice.log.11March2018
11048 From logs it is evident non-uniform choice function defined as previously approximately simulates the bias and almost
11049
11050
11051 521. (THEORY and FEATURE-DONE) SAT Solver Update - Non-Uniform Choice - 3200 variables and 3100 clauses and Alpha=4.2
11052 - 12 March 2018
11053 -----
11054 SAT Solver has been updated for some aesthetics - literal selection in non-uniform choice has been parametrized: sequ
11055 based on how three random literals are chosen per random 3SAT clause - sequentially as 3*nP1 or simultaneously as nF
11056 observed between these two choices. Number of variables is set to 3200 and clauses to 3100. LSMR iteration has been i
11057 reduced to 10. For few random 3SATs, observed MAXSAT approximation ratio average stands at ~95%. This accuracy has b
11058 where a phase transition occurs from easy-to-hard. Number of unsatisfiable formulae increase for alpha > 4.26. MAXSAT
11059
11060 References:
11061 -----
11062 521.1 SAT Solvers and Phase Transition at Alpha=4.26 [Clause/Variable Ratio] - [Carla P. Gomes, Henry Kautz, Ashish S
11063
11064
11065 522. (THEORY and FEATURE-DONE) SAT Solver Update - Non-uniform Choice 2 - 5000 variables and Alpha=4.267 and some int
11066 - 15 March 2018
11067 -----
11068 SAT Solver has been updated for a new nonuniform choice function nonuniform_choice2() which has following algorithm:
11069 - Each permutation nPn of length n is elongated to n*n*alpha length array by replicating a non-variable X of
11070 - Literals are chosen from this new array as (n*n*alpha)P1 or (n*n*alpha)P3 in a while loop till a valid lite
11071 - This creates a probability of fraction n/(n*n*alpha)=1/(n*alpha) for per literal choice.
11072 But this implementation was found to be no different from nonuniform_choice() which chooses a submatrix in per litera
11073

```

```

11074| Here the intuition on how LSMR/LSQR works has to be mooted - Each binary assignment string can be thought of as a ste
11075|   -----
11076|   |   |
11077|   -----
11078| where troughs represent 0s and peaks 1s. LSMR/LSQR finds a set of real valued points on a sinusoidal polynomial which
11079|
11080| Probability of an LSMR/LSQR real-to-binary round off assignment failing to satisfy a random 3SAT:
11081| -----
11082| For each binary variable  $x_i$ , LSMR/LSQR creates a real value which is rounded off as:
11083|    $x_i = 0$  if  $x_i < 0.5$ 
11084|    $x_i = 1$  if  $x_i > 0.5$ 
11085| This round off can fail if:
11086|    $x_i = 1$  if  $x_i < 0.5$ 
11087|    $x_i = 0$  if  $x_i > 0.5$ 
11088|
11089| Lovasz Local Lemma Analyses described earlier further explain the clause-variable dependency graph(Factor graph) scer
11090|
11091| -----
11092| 523. (THEORY and FEATURE-DONE) SAT Solver Update - Variables and Alpha as parameters and two Alpha Versus MAXSAT rati
11093| related to 522 - 16 March 2018
11094| -----
11095| SAT Solver has been updated to accept commandline parameters of number of variables and Alpha (Clause/Variable ratio)
11096|   $python CNFSATSolver.py <number_of_variables> <alpha>
11097| Some debug prints have been changed. Following sets of SATs were solved and variation of MAXSAT approximation ratio v
11098| captured as graph (for nonuniform_choice()):
11099|
11100| Number of Variables - 600 (after atleast 15 random 3SAT iterations)
11101| -----
11102| Alpha          Observed MAXSAT Approximation Ratio
11103| -----
11104| 1              94.5%
11105| 2              92.7%
11106| 3              91.5%
11107| 4              90.74%
11108| 4.267         90.45%
11109| 5              90.28%
11110| 6              90.25%
11111| -----
11112| Number of Variables - 300 (after atleast 15 random 3SAT iterations)
11113| -----
11114| Alpha          Observed MAXSAT Approximation Ratio
11115| -----
11116| 1              95%
11117| 2              93%
11118| 3              92%
11119| 4              90.6%
11120| 4.267         90.6%
11121| 5              90.49%
11122| 6              90.73%
11123|
11124| Logs for an iteration of 5000 variables and Alpha=4.267 has been committed to python-src/testlogs/CNFSATSolver.5000va
11125| -----
11126| SAT Solver has been updated for a new nonuniform_choice3() function based on an Epsilon Bias Test Snippet EpsilonBias
11127|
11128| -----
11129| 524. (THEORY and FEATURE-DONE) SAT Solver Update - nonuniform_choice3() updated for constant multiple in expansion of
11130| - 19 March 2018 - related to 523
11131| -----
11132| 1. CNFSATSolver.py nonuniform_choice3() has been changed to expand the variables array by following relation:
11133|    $n + x = n * \sqrt{\alpha}$ 
11134|    $x = n * (\sqrt{\alpha} - 1)$ 
11135|   => array of n variables is expanded to array of size  $n * (\sqrt{\alpha} - \text{damp})$  for alpha = number_of_clauses/numbe
11136| 2. damp variable has been hardcoded to 2 than 1 which approximates theoretical  $1/\sqrt{m*n}$  probability well because c
11137| 3. This expansion creates an approximate nonuniform probability  $1/n * \sqrt{\alpha}$  per literal excluding replicated skew
11138| filtered in the while loops
11139| 4. Example SAT Solver logs for 1000 variables and Alpha=4.267 has been committed to python-src/testlogs/CNFSATSolver.
11140| 5. MAXSAT Approximation ratio again is 90-91% for 20+ random 3SATs and nonuniform per literal probability almost matc
11141| (till penultimate decimal)
11142|
11143| -----
11144| 525. (THEORY) Counterexample in Majority Voting, Timeline Evolution of Belief Propagation, Intrinsic Merit - related
11145| -----
11146| Previous sections described a counterexample in Majority Voting for a question:
11147|   "Did an artefact exist millenia ago?"
11148| There are two possible answers: Yes and No which depend on intrinsically determining truth of answer to this questior
11149|
11150| -----
11151| 526. (THEORY and FEATURE-DONE) Hardy-Ramanujan Approximate Ray Shooting Queries for Factors - Optimization in Computa
11152| Factorization - 21 March 2018 - related to 487
11153| -----
11154| 1. Ray Shooting Queries based on Hardy-Ramanujan Theorem for Normal Order of number of factors of an integer has been

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11155 new function.
11156 2. Each approximate factor is queried by a ray from origin of slope tan(m*pi/(2*k*loglogN)) intersecting hyperbolic a
11157 sqrt(N/[tan(m*pi/(2*k*loglogN))])-1 for m=1,2,3,...,kloglogN
11158 3. Two integers have been factorized using local tile search and comparison between approximate factors and actual fa
11159 python-src/testlogs/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.HardyRamanujanRayShootingC
11160 python-src/testlogs/DiscreteHyperbolicFactorizationUpperbound_TileSearch_Optimized.HardyRamanujanRayShootingC
11161 4. Approximate Ray Shooting could be useful for integers having large value of factor multiplicity BigOmega (sum of p
11162 5. Constant k has been hardcoded presently and has to be heuristically found.
11163 6. Approximate Factors are helpful for sieving huge integers and binary search can be localized based on these approx
11164
11165 -----
11166 527. (FEATURE-DONE) Unsorted Search Update - Streaming Abstract Generator File Datasource Support, Prefix-Suffix subs
11167 - 23 March 2018
11168 -----
11169 1. Hardcoded File name in Streaming Abstract Generator has been replaced by a file name variable and file contents ar
11170 stripped of leading and trailing whitespaces and yielded.
11171 2. Padding of '#' in Unsorted Search has been replaced by '0'. Revised Unsorted Search Algorithm in https://github.com
11172 3. New function to print contents of all hashtables has been added.
11173 4. Function create_prefix_suffix_hashtables() initializes prefix and suffix hashtables for strings from Streaming Abst
11174 5. search_number() function has been rewritten to search for all prefixes and suffixes hashtables and match True/False
11175 6. New input file First100Primes.txt has been created.
11176 7. Primes and Non-Primes are lookedup and logs has been committed to testlogs/UnsortedSearch.log.23March2018
11177
11178 -----
11179 528. (THEORY) Consensus, Pareto Optimality, Intrinsic-Perceived Value/Merit Equilibrium, Fair Division, Multiple Ager
11180 Intrinsic Fitness/Merit and Perceived Merit Equilibrium has been described earlier as an approximate consensus measur
11181 merit of an entity. Consensus problem for absolute intrinsic merit arises in the following context of Fair Division w
11182 to be allocated amongst multiple agents fairly (also known as MARA-Multi Agent Resource Allocation). Fairness in allc
11183 For a utility function u:(Good,Agent)→Happiness, set of agents (x1,x2,x3,...,xn) and goods/services/resources (r1,r2
11184 Most obvious application of Pareto Optimality is Pricing or Determining Value of Goods. Allocation is Envy-Free if nc
11185
11186 Traditional Ranking methodology followed is to compute ranking scores per website URL independent of other URLs i.e  $\epsilon$ 
11187
11188 References:
11189 -----
11190 528.1 MARA Survey - https://staff.science.uva.nl/u.endriss/MARA/mara-survey.pdf
11191
11192 -----
11193 529. (THEORY and FEATURE-DONE) Recursive Lambda Function Growth - Graph Tensor Neuron Network Intrinsic Merit for Ra
11194 - Analysis for different text - 26 March 2018
11195 -----
11196 1. Text input for Recursive Lambda Function Growth has been updated
11197 2. Graph Tensor Neuron Network Intrinsic Merit for Lambda Function Composition of Random Walks of Definition Graph ha
11198 log testlogs/RecursiveLambdaFunctionGrowth.log.GraphTensorNeuronNetwork.26March2018
11199 3. Maximum Graph Tensor Neuron Network Intrinsic Merit occurs for Random Walk Composition:
11200 grow_lambda_function3(): Maximum Per Random Walk Graph Tensor Neuron Network Intrinsic Merit :
11201 u'('housing(protective,(certain(zone,(something(target,(part(include,(urban(area,(Chennai(city,formerly))))))))))))',)
11202 4. Top percentile Unsupervised Classes of this text by Dense Subgraph Discovery (Core Numbers) are:
11203 =====
11204 Unsupervised Classification based on top percentile Core numbers of the definition graph(subgraph of WordNet)
11205 =====
11206 This document belongs to class: arsenic ,core number= 16
11207 This document belongs to class: Greenwich_Village ,core number= 14
11208 This document belongs to class: state_of_matter ,core number= 14
11209 This document belongs to class: order ,core number= 14
11210 This document belongs to class: include ,core number= 10
11211 This document belongs to class: part ,core number= 10
11212 This document belongs to class: exploitation ,core number= 9
11213 This document belongs to class: area ,core number= 9
11214 This document belongs to class: three ,core number= 9
11215 This document belongs to class: collector ,core number= 8
11216 This document belongs to class: housing ,core number= 8
11217 This document belongs to class: January ,core number= 8
11218 This document belongs to class: Trey ,core number= 8
11219 This document belongs to class: Chennai ,core number= 7
11220 This document belongs to class: urban ,core number= 7
11221 This document belongs to class: planning ,core number= 6
11222 This document belongs to class: zone ,core number= 6
11223 This document belongs to class: free-base ,core number= 6
11224 This document belongs to class: travel ,core number= 6
11225 This document belongs to class: one ,core number= 6
11226 This document belongs to class: target ,core number= 6
11227 This document belongs to class: something ,core number= 6
11228 This document belongs to class: republic ,core number= 6
11229 This document belongs to class: government ,core number= 5
11230 This document belongs to class: legal_power ,core number= 5
11231 -----
11232 which reasonably coincide with the vertices of the maximum intrinsic merit random walk and capture the Legal/Governat
11233 of the text(though there are WordNet anomalies printing 'arsenic' etc., as classes. These anomalies are caused becaus
11234
11235

```

```

11236 Essence:
11237 -----
11238 Meaning of a text is approximated as:
11239     - Create a Definition Graph Representation of Text from some Ontology
11240     - Do random walks/Hamiltonian on the graph to simulate the human text comprehension
11241     - Get classes of the text from Recursive Gloss Overlap Unsupervised Classifier
11242     - Compute Lambda Composition Trees for all random walks in definition graph
11243     - These random walk lambda composition trees are approximations of all possible meanings of the text
11244     - Compute Graph Tensor Neuron Network Intrinsic Merit for all random walk lambda composition trees
11245     - Lambda Composition Tree of Maximum Graph Tensor Neuron Network Intrinsic Merit is the most likely approxima
11246     - This is obvious because this maximum merit tree has Neuron Tensor Network Relations of maximum similarity/t
11247 these similarities are composed and belief propagated
11248 -----
11249 -----
11250 530. (FEATURE-DONE) Recursive Lambda Function Growth - Simple Cycles and Rich Club Coefficient - 27 March 2018
11251 -----
11252 1.Recursive Lambda Function Growth implementation has been updated to loop through cycles in the definition graph of
11253 between Cycles and Random Walks by a boolean flag ClosedPaths.
11254 2.Closed Paths or Cycles simulate the meaning better and the tree lambda composition obtained from cycle vertices has
11255 found to approximate meaning more closely.
11256 3.Logs for this has been committed to testlogs/RecursiveLambdaFunctionGrowth.log.GraphTensorNeuronNetwork.27March2018
11257 4.Rich Club Coefficients of the Definition Graph has been printed for each degree as a measure of connectivity of hig
11258 Rich Club Coefficient of the Recursive Gloss Overlap Definition Graph: {0: 0.004865591072487624, 1: 0.016526610644257
11259 5.Top core number classes from Unsupervised Recursive Gloss Overlap Classifier:
11260 -----
11261 ===== Unsupervised Classification based on top percentile Core numbers of the definition graph(subgraph of WordNet)
11262 =====
11263 This document belongs to class: incorporate ,core number= 4
11264 This document belongs to class: environment ,core number= 4
11265 This document belongs to class: regional ,core number= 4
11266 This document belongs to class: `in ,core number= 4
11267 This document belongs to class: component ,core number= 4
11268 This document belongs to class: exploitation ,core number= 4
11269 This document belongs to class: useful ,core number= 4
11270 This document belongs to class: relating ,core number= 4
11271 This document belongs to class: unit ,core number= 4
11272 This document belongs to class: particular ,core number= 4
11273 This document belongs to class: making ,core number= 4
11274 This document belongs to class: process ,core number= 4
11275 This document belongs to class: sphere ,core number= 4
11276 This document belongs to class: something ,core number= 4
11277 This document belongs to class: goal ,core number= 4
11278 This document belongs to class: farm ,core number= 4
11279 This document belongs to class: urbanization ,core number= 4
11280 This document belongs to class: strategic ,core number= 4
11281 This document belongs to class: ' ,core number= 4
11282 This document belongs to class: increase ,core number= 4
11283 This document belongs to class: comforts ,core number= 4
11284 This document belongs to class: city ,core number= 4
11285 This document belongs to class: district ,core number= 4
11286 This document belongs to class: farming ,core number= 4
11287 This document belongs to class: urban ,core number= 4
11288 This document belongs to class: way ,core number= 4
11289 This document belongs to class: plan ,core number= 4
11290 This document belongs to class: do ,core number= 4
11291 This document belongs to class: contain ,core number= 4
11292 This document belongs to class: see ,core number= 4
11293 This document belongs to class: state ,core number= 4
11294 This document belongs to class: region ,core number= 4
11295 This document belongs to class: proposal ,core number= 4
11296 This document belongs to class: life ,core number= 4
11297 This document belongs to class: decisiveness ,core number= 4
11298 This document belongs to class: lives ,core number= 4
11299 This document belongs to class: metropolitan ,core number= 4
11300 -----
11301 coincide reasonably well to the Maximum Merit Cycle as below and the meaning of the text can be inferred from the com
11302 -----
11303 Cycle : [u'particular', u'regional', u'region', u'something', u'see', u'make', u'plan', u'goal', u'state', u'city', u
11304 Cycle Composition Tree for this cycle : (u'particular)((region(regional,(see(something,(plan(make,(state(goal,(urban(c
11305 maximum_per_random_walk_graph_tensor_neuron_network_intrinsic_merit= (u'(regional(particular,(`in(region,(pronounce(w
11306 -----
11307 grow_lambda_function3(): Graph Tensor Neuron Network Intrinsic Merit for this text: 3804.34147246
11308 6.NetworkX library has been upgraded to recently released version 2.1
11309 -----
11310 -----
11311 531. (THEORY-FEATURE-DONE) Least Squares SAT Solver Benchmarks - 1000 variables - Non-uniform choice 3 - different va
11312 -----
11313 1. SAT Solver (LSMR) has been benchmarked for 1000 variables and for varying values of Alpha as below. MAXSAT approxi
11314 atleast 20 iterations of random 3SAT for nonuniform_choice3() are:
11315 Alpha = 1 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 94
11316 Alpha = 2 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 92

```

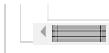
```

11317 Alpha = 3 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 91
11318 Alpha = 4.267 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far
11319 Alpha = 5 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 89
11320 Alpha = 6 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 89
11321 Alpha = 7 - Observed - MAXSAT-APPROXIMATION Ratio - Moving Average Percentage of Clauses per CNF satisfied so far: 89
11322
11323 2. As usual for equal variable-clauses MAXSAT ratio is the maximum at 94-95% and decreases for increasing alpha. For A
11324
11325 3. Log excerpts have been captured in testlogs/CNFSATSolver.1000variablesDifferentAlphasBenchmarks.29March2018
11326
11327 -----
11328 532. (THEORY) Packing/Filling/Tiling problems, Complement Functions/Diophantine Equations, Ramsey Coloring,
11329 Exact Cover, Matiyasevich-Robinson-Davis-Putnam Theorem - related to 462,463,491 - 19 April 2018
11330 -----
11331 As mentioned in previous sections, complement functions are subsets of set of Diophantine Equations defining
11332 each diophantine set in an exact cover - this generalizes definition of complement functions to exact cover of size c
11333
11334 Reference:
11335 -----
11336 532.1 Pentominoes Tiling Exact Cover for Chess board - https://en.wikipedia.org/wiki/Exact\_cover - Each pentomino til
11337 532.2 Euclidean Ramsey Theory - http://www.math.ucsd.edu/~ronspubs/pre\_Euclidean.pdf - [RL Graham] - Euclidean Ramsey
11338
11339 -----
11340 533. (THEORY and FEATURE-DONE) Complement Diophantine and Factorization - Pell Equation Solver Update -
11341 20 April 2018
11342 -----
11343 1. Complement Function Implementation has been updated to invoke sympy Pell Equation solver for some N and D
11344 in  $x^2 - D*y^2 = N$ 
11345 2. Factorization reduces to integer solutions of Pell Equation but the converse is harder - factors must be known
11346 a priori as  $pq = N$  from some factoring algorithm. Then following equations can be solved:
11347  $x + \sqrt{D}y = p$ 
11348  $x - \sqrt{D}y = q$ 
11349 for x and y.
11350
11351 log excerpts:
11352 =====
11353 Pell Diophantine Equation - Factorization reduces to solving Pell's Equation (for some N)
11354 =====
11355 Solution for Pell Equation :  $x^2 - 91*y^2 = 1$  :
11356  $(1574 + \sqrt{1})/165 * (1574 - \sqrt{1})/165 = 91$ 
11357
11358 -----
11359 534. (THEORY and FEATURE-DONE) Complement Diophantine and Factorization - Pell Equation Solver Update 2 -
11360 20 April 2018
11361 -----
11362 1. Complement Function Implementation has been updated to invoke sympy Pell Equation solver for some N and D
11363 in  $x^2 - D*y^2 = N$  for D=1
11364 2. Following are the factors p,q of N:
11365  $x + y = p$ 
11366  $x - y = q$ 
11367 for Pell equation solutions x and y. This is exponential in number of bits of N and equivalent to most
11368 Number Field Sieve algorithms for Factorization in vogue. Computational Geometric Factorization in NC
11369 implies x and y can be found in parallel polynomial time (which is quite surprising given the antiquity and
11370 notorious difficulty of this ~1500 year old problem).
11371 3. Pell's Equation for Factoring and Prime polynomials (e.g Matiyasevich, Jones-Sato-Wada-Wiens) are thus
11372 complement diophantines representing the exact cover {Primes,Composites} of the Set of Natural Numbers
11373
11374 log excerpts:
11375 =====
11376 Pell Diophantine Equation - Factorization reduces to solving Pell's Equation (for D=1 and some N)
11377 =====
11378 Solution for Pell Equation :  $x^2 - 1*y^2 = 989295$  :
11379  $(1084 + 431) * (1084 - 431) = 989295$ 
11380
11381 -----
11382 535. (THEORY) Complement Functions, Complement Graphs, Ramsey coloring, Intrinsic Merit of Text-Graph -
11383 related to 2,338 - 21 April 2018
11384 -----
11385 Relations between the concept of complement functions and complement graphs have been described earlier in the
11386 context of Perfect Graph Theorem. This notion of complement graphs has direct application in graph representation of
11387
11388 There is a known theorem which states that if a graph G is disconnected its complement G's is connected and vice-vers
11389
11390 References:
11391 -----
11392 535.1 Introduction to Graph Theory - [Douglas B.West] - Perfect Graph Theorem for complement graphs, Ramsey Theorem f
11393
11394 -----
11395 536. (FEATURE-DONE) ConceptNet Client Upgrade to 5.6 - REST endpoints for Emoticons - 23 April 2018
11396 -----
11397 1. ConceptNet Client has been updated for new REST endpoints in ConceptNet 5.6

```

11398 2. Function for querying emotions has been added for new emoji endpoints in ConceptNet 5.6
11399 3. logs for this have been committed to testlogs/ConceptNet5Client.log.23April2018

11401 -----
11402 537. (THEORY) Shell Turing Machines, Word2Vec and Intrinsic Merit - 24 April 2018 - related to 42
11403 -----
11404 Shell Turing Machines described earlier are experimental enhancements to Turing Machine definition which
11405 introduces dimension as a parameter in addition to tapes, alphabets, head etc., Adding dimension to Turing
11406 Machines has immense applications and simulates lot of real world computations which span across multiple
11407 dimensions. For example a Turing Machine defined in dimension d+1 has more computational power than a machine
11408 defined in dimension d i.e $L(T(d))$ is in $L(T(d+1))$. This is a dimensional hierarchy as opposed to Time and Space
11409 hierarchies of Turing Machines. This has striking applications in graph representation of texts. Each word
11410 vertex in a definition graph G_1 can be represented as a vector in a space of dimension d. Word2Vec embeddings
11411 (e.g ConceptNet) already implement this by mapping each word to a vector in space of some dimension.
11412 Then another definition graph G_2 of words defined on a vector space of dimension d+1 can elicit more meaning
11413 from text than G_1 . Recursive Lambda Composition Trees for G_1 and G_2 are two Turing-equivalent computation models
11414 approximating the meaning - G_2 approximates better than G_1 . In other words intrinsic merit computed for G_2 is
11415 more accurate than G_1 for same text. Present algorithms for Recursive Gloss Overlap and Recursive Lambda
11416 Function Growth do not affix dimension information for word vertices.



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