



Probabilistic password generators

(and fancy curves)

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- ▶ I am no mathematician
- ▶ Conclusions might be erroneous
 - ▶ Bugs !
- ▶ All conclusions are relative to public leaks, specifically the 2012 Yahoo Contributor Network leak
 - ▶ 453491 distinct passwords
 - ▶ 342514 unique passwords
 - ▶ Unique passwords used, to reduce biases (and introduce new ones, hopefully less problematic)
- ▶ The training set is the rockyou list

A technique for generating candidate passwords from a statistical model

Notations

$P(x)$ probabilistic distribution of all characters at position x

$p(x, y)$ probability that the character at position x is y

$c(x)$ character at position x

$P'(x)$ $\lfloor -K.\log(P(x)) \rfloor$

$p'(x, y)$ $\lfloor -K.\log(p(x, y)) \rfloor$

$\Psi(pass)$ probability that a password is chosen

It is common to store log-probabilities instead of raw probabilities. The reason for rounding them will be apparent later. Please note that:

- ▶ A likely event will have a P value close to 1, and a P' close to 0
- ▶ $P_1.P_2.P_3$ will turn onto $P'_1 + P'_2 + P'_3$
- ▶ P' is nicer to look at than P

Examples

$P(x)$ is a function of	Cracking paradigm
Nothing (constant)	Naive exhaustive search, standard rainbow tables, frequency optimized search
$c(x - 1)$	JtR Markov mode
$c(x - 2), c(x - 1), x, l$	JtR incremental mode, for each length l
$c(x - 1), x$	Hashcat per position Markov mode ?

Some distributions have special properties. This talk will focus on distributions that are only functions of the previous characters (ie. can be modeled as *Markov chains*). They can be written as :

$$P(x) = f(c(x - 1), c(x - 2), \dots, c(0), x)$$

- ▶ Find a model that fits well with real world password selection
- ▶ Compute the parameters that fit a training set
- ▶ Generate all candidate passwords that satisfy some condition and use them for cracking
 - ▶ Every per-character log-probability of occurrence is less than a given threshold
 - ▶ The sum of the log-probabilities of each character in a candidate password is less than a given threshold (we will only consider this case)

Model

- ▶ $\Psi(\text{pass}) = p(0, p) * p(1, a) * p(2, s) * p(3, s)$
- ▶ $\Psi'(\text{pass}) = p'(0, p) + p'(1, a) + p'(2, s) + p'(3, s)$
- ▶ For a maximum probability ψ , generate and crack all $\{p \mid \Psi'(p) < \psi'\}$

We can think of ψ' as a *budget* to spend on individual p'

These probability distributions have the following nice properties:

- ▶ It is possible to count the number of words p satisfying $\Psi'(p) < \psi'$ (called *nbparts*)
 - ▶ Actually it is possible to enumerate many related values
- ▶ Once done, it is easy to generate the n^{th} password (this is important for rainbow tables and distributed computing)
- ▶ It is possible to quickly compute $\Psi'(p)$ for arbitrary passwords provided that we give v , $\forall(x, y) \in \{p(x, y) = 0\}, p'(x, y) = v$
 - ▶ We can compute *nbparts* for every value of p , thus estimate how long it would take to crack this password using this model
 - ▶ Yes, that means you can fill your reports with curves

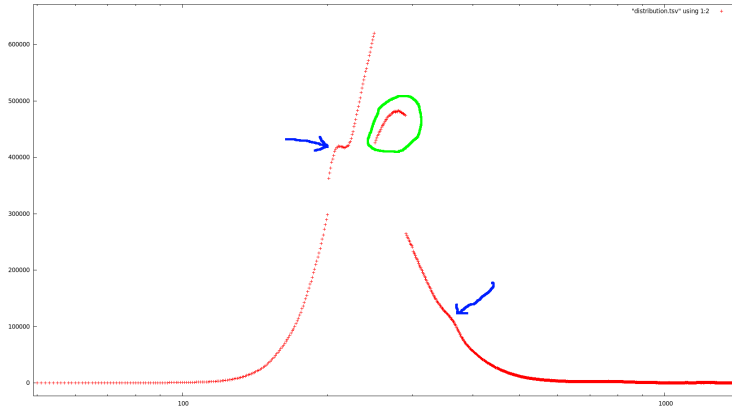


Figure: Passwords found per maximum ψ'

- ▶ Partial results, ran Markov 290 (explains the second drop)
- ▶ Multiple humps, typical of frankencurves
- ▶ Huge drop after the peak at 250. Are there Markov generated passwords ?

State definition

Let's use $P(x) = f(c(x - 1))$, ie. JtR Markov mode

- ▶ The *reduced* state is the previous character
- ▶ The *full* state is the tuple (previous character, remaining *budget*, remaining length)
- ▶ Initial *full* state could be $(\emptyset, 100, 10)$

Training set

- ▶ abc
- ▶ aaa
- ▶ bac
- ▶ ccab

Take advantage of the state machine structure:

- ▶ Build the state transition graph (*reduced* state)
- ▶ Map all *full* states into *reduced* states
- ▶ Map all *reduced* states into *full* states that could be derived from it
- ▶ Start with the initial *full* state
- ▶ From a full set, compute the reduced set, and recursively run this step for all valid derived *full* states
 - ▶ When the function finishes, store the (*full* state, password count) pair for caching
 - ▶ Exploit node collisions (thanks to the rounding)
 - ▶ Memory and time usage orders of magnitude lower than password count

Inner state transition

n	$c(x-1)$	$c(x)$	$p' = \lfloor -10 \cdot \ln(p(x, c(x) c(x-1))) \rfloor$
0		a	6
0		b	13
0		c	13
> 0	a	a	9
> 0	b	a	6
> 0	a	b	9
> 0	c	a	6
> 0	a	c	16
> 0	b	c	6
> 0	c	c	6

Computing nbparts – state machine

Password generation can be modeled as a state machine:

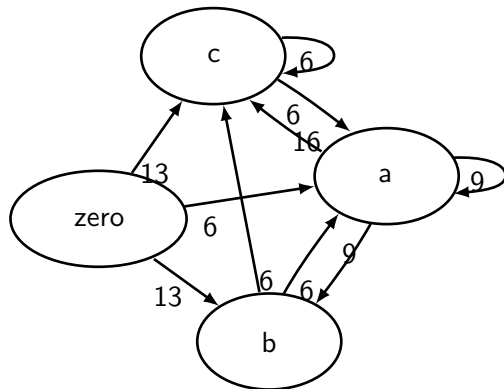
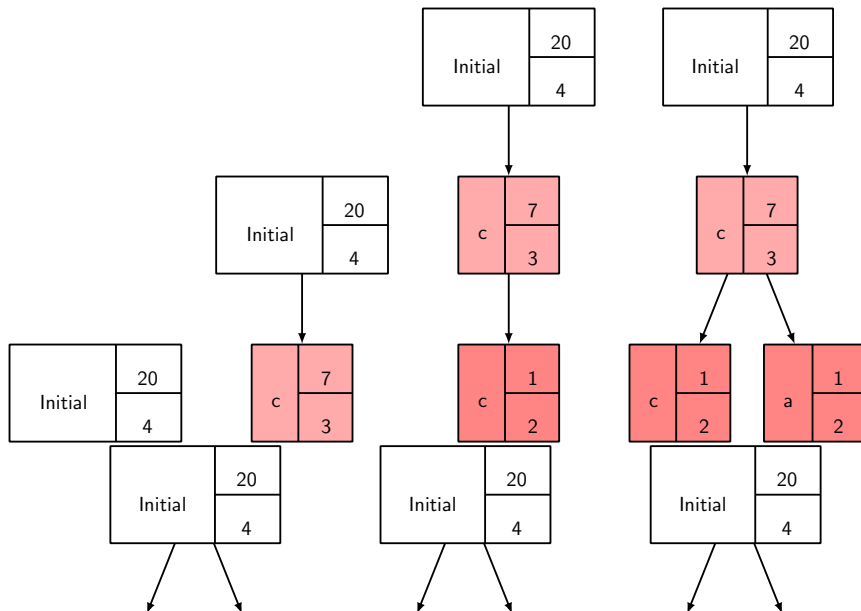


Figure: The resulting state machine

1. We start with an empty *reduced* state, $\psi' = 100$, length *budget* of 10, and $nbparts = \emptyset$. The *full* state is $(\emptyset, 100, 10)$
2. The list of acceptable next *reduced* states is $(a, 6), (b, 13), (c, 13)$
3. Start with $(a, 6)$. The next *full* state is $(a, 94, 9)$. It is not in $nbparts$, so the algorithm keeps going
4. Continue until the length or budget is depleted
5. Store the password count related to this node in $nbparts$

With this training set, 621 nodes will be generated, and the result will be 58314 passwords

Computing nbparts



Known optimization (cf. "mask mode", Weir thesis)

- ▶ Password is made of subsequent characters of the same class (upper, lower, digits, special)
- ▶ Can be modeled as a Markov thingy. For example, `pass123` can be modeled as:
 - ▶ A chain of types [Lower, Digit] – the "no length" model
 - ▶ A chain of types with length [Lower 4, Digit 3] – the "part type and length" model
- ▶ Each part can be modeled as previously
- ▶ $\Psi'_p(\text{pass123}) = B \cdot \Psi'([L4, D3]) + \Psi'(\text{pass}) + \Psi'(123)$
 - ▶ B is a constant that must be tuned

Much harder! Will be written $nbparts_p$ (for *patterns*)

- ▶ Generate the $nbparts$ graph for patterns, *but*:
 - ▶ At each node, have intermediate states, one for each point of remaining budget
 - ▶ Compute the sub-part $nbparts$ for each of these states
 - ▶ And multiply by the $nbparts_p$ of the next nodes

Same procedure as before, but for patterns. Let's say we pick $U4$, and have a "budget" of 20

- ▶ Generate 18 intermediate states, from 1 to 19
- ▶ For each state i , "spend" i on a 4 uppercase letters subpart, and $20 - i$ for the remaining parts
 - ▶ let $n_i = nbparts(\Psi' = i, length = 4)$
 - ▶ let S be the state of valid next *full* states
 - ▶ $n_i = \sum_{s \in S} nbparts_p(\Psi' = n - i, s)$
 - ▶ $nbparts_{p,i} = (n_i + 1)next_i$
- ▶ $nbparts_p = \sum_{i=1..19} nbparts_{p,i}$

How to compute $nbparts(P' = i, length = 4)$? All we can do is $nbparts(P' \leq i, length \leq 4)$!

- ▶ Pretty obvious when written like this. Took me two days to realize ...
- ▶ $nbparts(P' = i, length \leq 4) = nbparts(P' \leq i, length \leq 4) - nbparts(P' \leq i - 1, length \leq 4)$
- ▶ Same reasoning for fixing the length. Beware of edge cases

Main loop – is there a bug ?

```

calcpatternsnbparts' malus !gtype !stats stt@(LvlState _ !curlvl !curstate) !curparts !ns !snbparts = let
!correctstates = filter (\(_,l) -> l <= (curlvl `div` malus)) $! curstates ns gtype curstate
gennext (mp, c) su =
  let (s,lnomalus) = downgrade gtype su
      l = lnomalus * malus
      remaining = curlvl - l
      (Pattern nextStateType nextStateLen) = getNextState su
      nbpartsmap = snbparts Map.! nextStateType
      gm 0 _ = 0
      gm _ 0 = 1
      gm ln v =
        let lo | ln >= 32 = HM.lookup (LvlState 31 v NoState) nbpartsmap
              | otherwise = HM.lookup (LvlState ln v NoState) nbpartsmap
        in case lo of
          Just !x -> x
          Nothing -> error $ "Would not find " ++ show (l, v)
      getnbparts 0 = 0
      getnbparts lv = ( gm nextStateLen lv - gm (nextStateLen-1) lv ) -
                      ( gm nextStateLen (lv-1) - gm (nextStateLen-1) (lv-1) )
      levelsToTry = [ (lv, getnbparts lv) | lv <- [1..remaining] ]
      trylevel (tnmp, tnc) (tlvl, tnbparts) = let
        (nmp, nnc) = calcpatternsnbparts' malus gtype stats (LvlState 0 (remaining - tlvl) s) tnc ns snbparts
        !res = tnc+(nnc+1)*tnbparts
      in (nmp, res)
      (nmp, nc) = foldl' trylevel (mp, 0) levelsToTry
  in (nmp, c+nc)
(!nm, !count) = foldl' gennext (curparts, 0) correctstates
in case HM.lookup stt curparts of
  Just x -> (curparts, x)
  Nothing -> (HM.insert stt count nm, count)

```

Frequency optimized exhaustive search

- ▶ Search all passwords made with a charset of n elements
- ▶ Start with the shortest passwords and most frequent characters
- ▶ What is the best value for n ?
- ▶ For my sample, 36: ae1iorns21t0m3dc9hu847by56kgpwjfvzxq

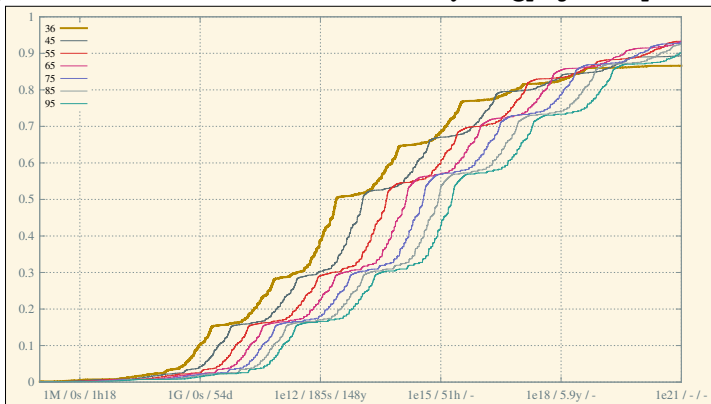


Figure: Passwords found per candidates tested, for various charset length

Markov like modes : Model Structure/Subpart/B value

- ▶ Markov mode:
 - ▶ M1 : Markov using the previous item (an item is a character or a part template)
 - ▶ M2 : Markov using the two previous items
- ▶ Model type:
 - ▶ No model
 - ▶ Model part *type* and length
 - ▶ Model part *type* only
- ▶ B value:
 - ▶ As explained previously, the "score" of a password is the sum of the scores of all subparts, plus B times the score of the structure
 - ▶ $\Psi'_p(\text{pass}123) = B \cdot \Psi'([L4, D3]) + \Psi'(\text{pass}) + \Psi'(123)$

So, part/type/length M2/M2/B2 means:

- ▶ Each structure item is a (character type, length) pair
- ▶ Structure modeled with Markov using the two previous items
- ▶ Each part is modeled with Markov using the two previous characters
- ▶ Total cost is the sum of the costs of all parts plus twice the cost of the structure

Results – wordlists and mangling rules

- ▶ Used two widely used wordlists: wikipedia-sravec and rockyou
- ▶ Used a good and large list of mangling rules (see mangling rules presentation)
- ▶ Real world results are better, as word rejection hasn't been taken into account in the figures

Results – candidates tested / time spent

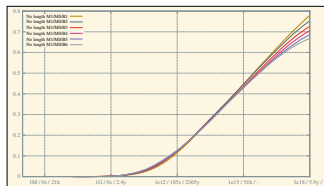
The following figures draw the ratio of passwords found per candidates tested, for various candidate generation methods

The x-axis ticks are labelled with : candidates tested / fast hash / slow hash

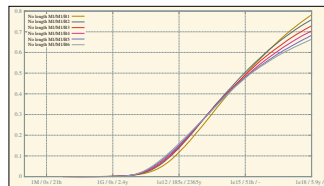
- ▶ The fast hash time is computed for 5400M c/s (oclHashcat, stock HD7970, 100k MD5 hashes)
- ▶ The slow hash time is computed for 1340 c/s (John the Ripper, 2 x X5650, 100 BCrypt \$2a\$08 hashes)

Count	MD5	BCrypt \$2a\$08
1e3	0s	74s
1e6	0s	20h 43m
1e9	0s	2y 133d
1e12	185s	2364y 285d
1e15	51h 26m	-
1e18	5y 317d	-

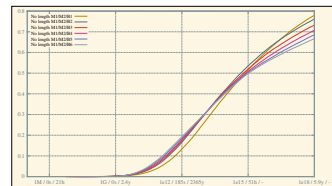
Comparing all values of B



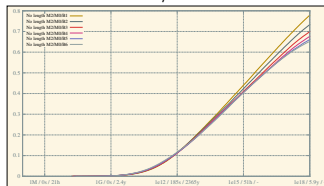
M1/M0



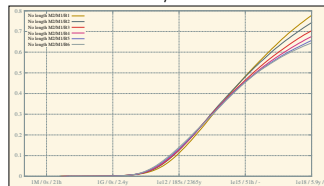
M1/M1



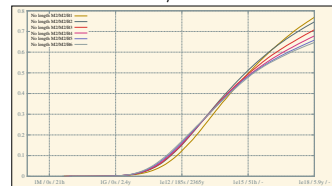
M1/M2



M2/M0



M2/M1



M2/M2

Results – part type only, best B

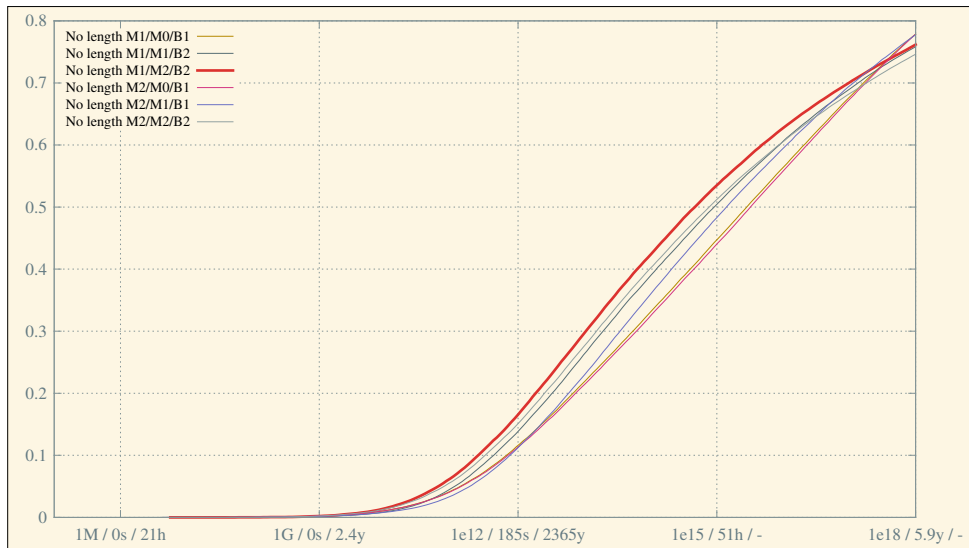
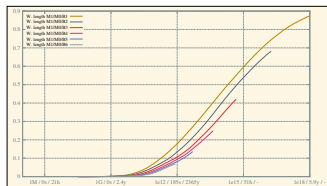
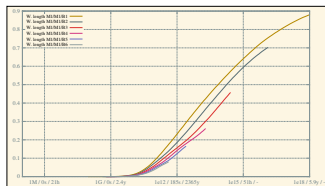


Figure: Passwords cracked per candidates tested.

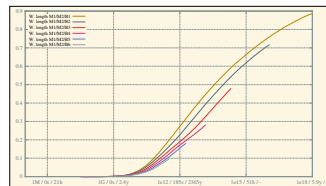
Comparing all values of B



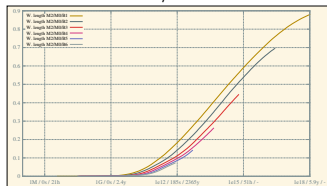
M1/M0



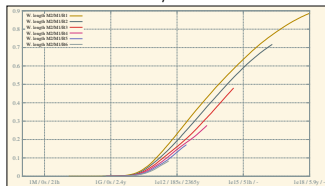
M1/M1



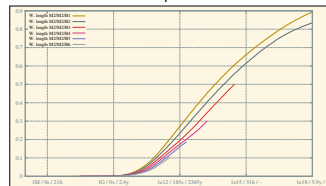
M1/M2



M2/M0



M2/M1



M2/M2

Results – part type and length, best B

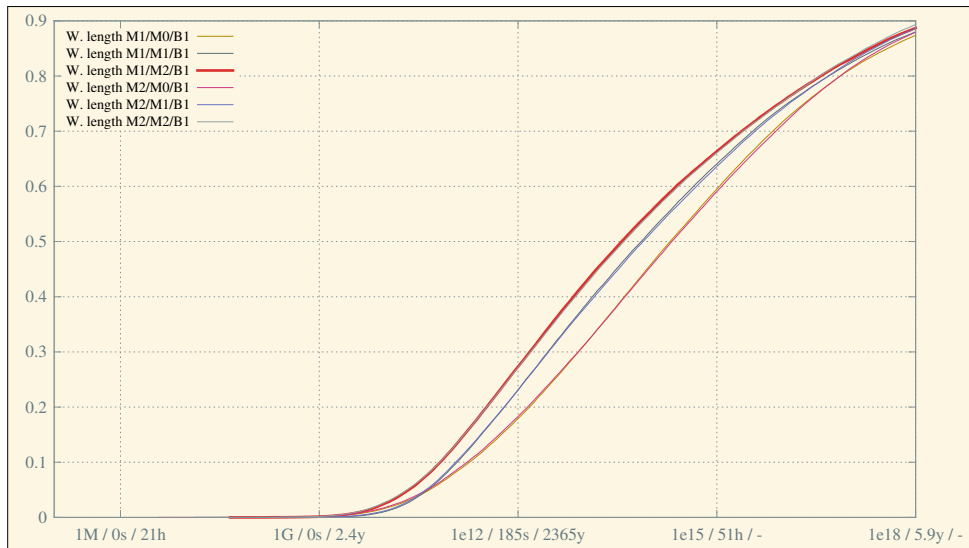


Figure: Passwords cracked per candidates tested.

Results – JtR incremental mode

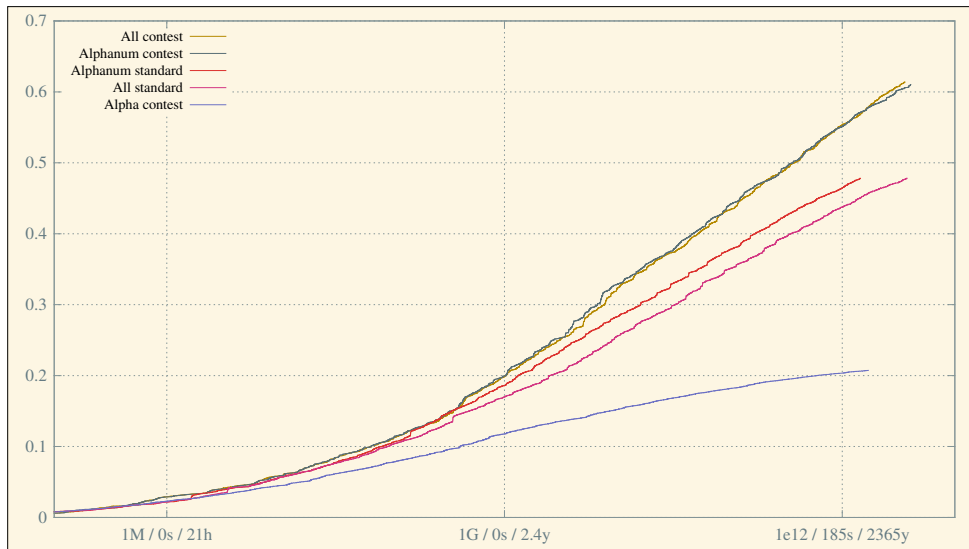
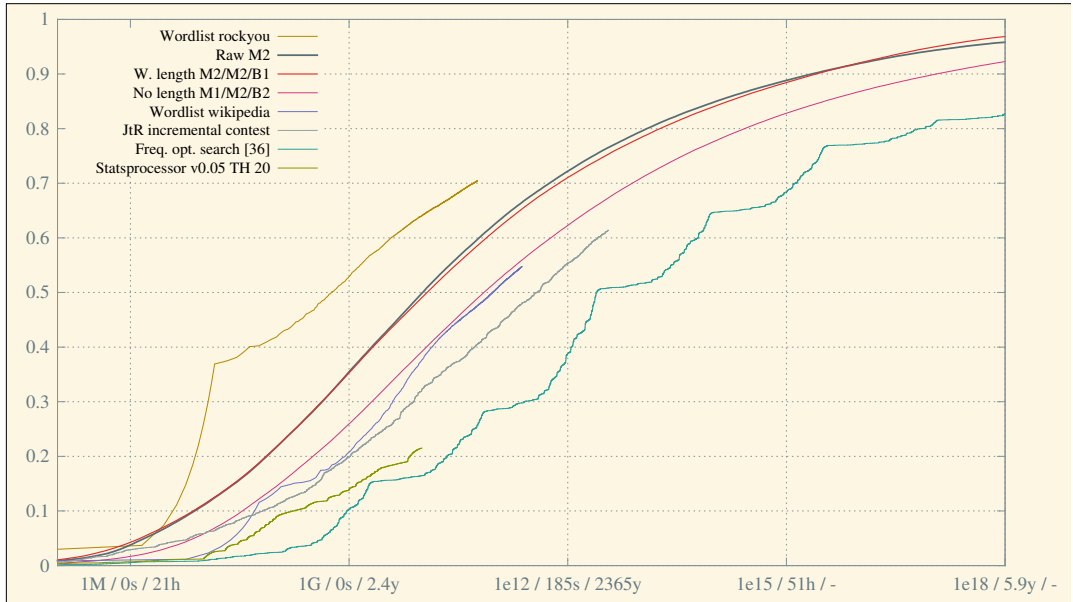


Figure: Passwords cracked per candidates tested.

Results – big picture



What about hard passwords?

A statistical generator is often used after a "wordlist" or "single" run. In order to account for this, the easiest passwords have been removed with the following steps:

- ▶ A selection of 754 rules from good sets (see the mangling rules presentation), against rockyou and wikipedia-sriveau
- ▶ A quick JtR Markov run (level 250, default shipped statistics)

The password count went from 342514 to 94990 (72% reduction)

Results – hard passwords

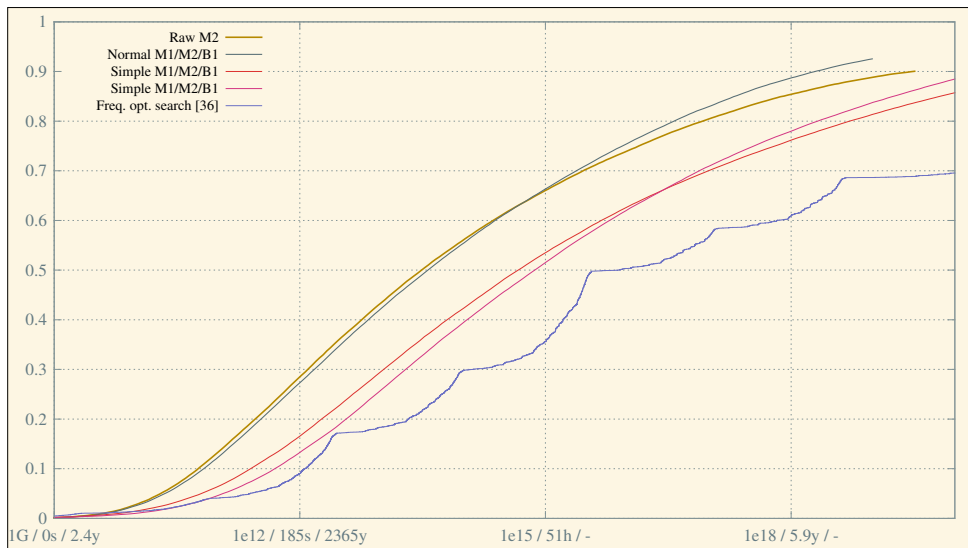


Figure: Passwords cracked per candidates tested, no trivial password

- ▶ The new model seems better when testing lots of passwords
 - ▶ Especially against "hard" passwords
 - ▶ Cracks a neglectable amount of passwords with little tests
 - ▶ Needs more benchmarks (fractional Bs)
- ▶ Guessing game:
 - ▶ What about implementation speed ?
 - ▶ Against Hashcat Bruteforce++ ?
- ▶ Soon:
 - ▶ JtR implementation
 - ▶ Perhaps a rainbow table implementation
 - ▶ More benches

Questions?

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