# **Pattern Matching with Mismatches and Wildcards**

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#### **Pattern Matching**

Given a text *T* and a pattern *P*, compute the occurrences of *P* in *T*.



Easy; a linear-time algorithm is known since 1970 [Morris-Pratt]. However, looking for exact matches of P in T might be too restrictive: think of spelling mistakes and corrupt data.

# **Pattern Matching with Wildcards**

Given a text *T* and a pattern *P*, which may contain wildcards  $(\Diamond)$ , compute the occurrences of *P* in *T*.



If we know the corrupt positions, we can replace their entries with wildcards  $(\Diamond)$ which match all letters of the alphabet and perform exact pattern matching. A long series of works has culminated in an elegant FFT-based  $\mathcal{O}(|T| \log |P|)$ -time algorithm [Clifford–Clifford; 2007].

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# **Pattern Matching with Mismatches**

Given a text *T*, a pattern *P*, and an integer threshold *k*, compute the sub-

strings of *T* that are at Hamming distance at most *k* from *P*.



Alternatively, we can look for substrings of *T* that are close to *P*, e.g., under the Hamming distance. This is a much harder problem; it admits an  $\tilde{\mathcal{O}}(|\mathcal{T}| + k \cdot \mathcal{O}(\epsilon)$ |*T*|/  $\sqrt{|P|}$ )-time solution [Gawrychowski–Uznanski; 2018].

## **Pattern Matching with Mismatches and Wildcards**

Given a text *T*, a pattern *P*, which may contain wildcards (♦), and an integer threshold *k*, compute the substrings of *T* that are at Hamming distance at most *k* from *P*.



In this work, we revisit the variant of problem where some of the corrupt positions are known.

$$
P \begin{array}{|c|c|c|c|c|} \hline \diamond \diamond & \diamond \diamond \diamond & \diamond & \diamond \diamond \diamond \\ \hline \end{array}
$$

$$
n = |T|, m = |P|
$$
  

$$
D = # \text{ wildcards} = 9
$$
  

$$
G = # \text{ groups of wildcards} = 4
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For wildcards in both *P* and *T*:

 $\tilde{\mathcal{O}}(n)$ √ *m − D*) [Amir-Lewenstein-Porat; 2004] O˜(*nk*) [Clifford-Efremenko-Porat-Rothschild; 2010]

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 [Amir-Lewenstein-Porat; 2004]  

$$
\tilde{O}(nk)
$$
 [Clifford-Efremenko-Porat-Rothschild; 2010]

#### For wildcards only in *P*:

$$
\tilde{\mathcal{O}}(n\sqrt{k}+n\cdot\min\{\sqrt[3]{Gk},\sqrt{G}\})
$$
  

$$
\mathcal{O}(n+(n/m)(D+k)(G+k))
$$

<sup>√</sup><sup>3</sup> *mk*) [Clifford-Porat; 2010] *G*}) [Nicolae-Rajasekaran; 2017] [this work]

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O˜(*n* <sup>√</sup><sup>3</sup> *mk*) [Clifford-Porat; 2010]  $k + n \cdot min$ {  $\frac{3}{3}$ *Gk*, √ *G*}) [Nicolae-Rajasekaran; 2017]  $\mathcal{O}(n + (n/m)(D+k)(G+k))$  [this work]

Fast when *D*, *G*, and *k* are small relative to *n*. For  $m = n/2$ ,  $k = G = n^{2/5}$ , and  $D=n^{3/5}$ , our algorithm takes  $\mathcal{O}(n)$  time, improving over  $\mathcal{O}(n^{6/5}).$ 



**Fact [folklore]** Given a pattern P of length m and a text T of length  $n \leq \frac{3}{2}m$  at least one of the following holds:

• The pattern *P* has at most one occurrence in *T*.



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The fragment of *T* spanned by *P*'s occurrences is periodic as well.

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The standard trick: Our assumption on the length of the text is not restrictive. If the text is much longer that the pattern, we can always consider separately  $\mathcal{O}(n/m)$  fragments of *T* of length  $\leq \frac{3}{2}m$  that overlap by  $m-1$  positions.

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This structural insight leads to an alternative  $\mathcal{O}(n+k^2)$ -time algorithm [CKW'20].

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The *k*-mismatch occurrences of *P* in *T* can be decomposed into  $\mathcal{O}((D+k)(G+k))$ arithmetic progressions. Lower bound:  $\Omega((D+k)(k+1))$ . What is the right answer?

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Bonus: A simple  $\mathcal{O}(n + DG)$ -time algorithm for exact PM with wildcards.

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Algorithm strategy: Find the exact matches of *C* in *T* and try to extend them to matches of *P*. We can verify in  $\mathcal{O}(G)$  time after  $\mathcal{O}(n)$ -time preprocessing.

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Observation: If the chunk *C* is aperiodic, its occurrences cannot overlap by more than  $|C|/2$  positions  $\Rightarrow$  at most  $n/(|C|/2) = \mathcal{O}(G \cdot n/m) = \mathcal{O}(G)$  occurrences.
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- Else, we have to work a bit more. :)

*P* a b ♢♦ ♢♦ ♢♦ b a a a b a b ♢♦ ♢♦ ♢♦ ♢♦ ♢♦ b a b a b a b ♢♦ ♢♦ ♢♦ ♢♦ a b

Setting: P matches a prefix of  $Q^\infty$ , where Q is a string that does not contain wildcards and is of length  $\mathcal{O}(m/D)$ .

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Adapted lemma from [CKW'20]: We can efficiently compute a substring *T* ′ of *T* that contains all occurrences of *P* and is at distance  $\mathcal{O}(D)$  from a prefix of  $\mathsf{Q}^\infty.$ 



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Conceptually, we slide P on T',  $|Q|$  positions at a time. There is an exact occurrence whenever all the misperiods on the sliding window are aligned with  $\diamond$ s.

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Conceptually, we slide P on T',  $|Q|$  positions at a time. There is an exact occurrence whenever all the misperiods on the sliding window are aligned with  $\diamond$ s.  $\mathcal{O}(DG)$  events yielding  $\mathcal{O}(DG)$  arithmetic progressions with difference  $|Q|$ .

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Observation: The misperiod in P must be aligned with one of the first  $D + 1$ misperiods in *T*. We thus have  $\mathcal{O}(D)$  candidates, and each can be verified in  $\mathcal{O}(G)$  time. Total time:  $\mathcal{O}(DG^2)$ .

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A helpful assumption: The *♦*s in *P* are well-spread around the chunk: every substring *U* of *P* that contains *C* has  $\mathcal{O}(|U| \cdot D/m)$   $\Diamond$ s.



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Exploiting it: As we compute misperiods in *T* one by one, we stop if they become too dense; our wildcards are sparse and hence cannot hide all of them.



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Amortisation: If while extending a *C*-run with misperiods, we reach another run that is synchronised (i.e., their starting positions differ by a multiple of the period), we do not need to process the latter *C*-run.

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A periodicity-based argument yields that we now need to verify  $\mathcal{O}(D)$  candidates over all *C*-runs! Total time: O(*DG*).

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Lemma: Let *V* be a binary vector of size *N* with  $M := ||V||$  1s. We can efficiently compute a large set  $U \subseteq [1 \dots N]$  such that for each  $i \in U$  and radius  $r \in [1 \dots N]$ , ∥*BV*(*i*,*r*)∥ ≤ 8*r* · *M*/*N*.

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We simply apply the above lemma with  $\Diamond$ s mapped to 1s and other letters mapped to 0s and then select the chunk so that it contains a position in *U*. We call such positions sparsifiers.

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We open the black-box of [CKW'20], ensure that some of the considered substrings contain sparsifiers, and refine the analysis.

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Large progression-free sets: For any sufficiently large *M*, there exists an integer  $n_M = \mathcal{O}(M2)$ √ log *M* ) and a progression-free set *S* such that *S* has cardinality *M* and *S* ⊆ [*nM*]. [Elkin'22]

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We use such sets to construct *P* and *T* such that *P* has  $\Omega((D + k) \cdot (k + 1))$ *k*-mismatch occurrences in *T* and no three occurrences form an arithmetic progression.

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Open problems:

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- Is the algorithm optimal?
- Close the gap on the number of arithmetic progressions.
- Edit distance instead of Hamming?
- More applications for sparsifiers?

**The End**

# Thank you for your attention!

Questions?

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