

FFTs in Graphics and Vision

Fast String Matching and Math Review

Fast Pattern Matching in Strings Knuth et al., 1977

Outline



Fast Substring Matching

Math Review

- Complex Numbers
- Vector Spaces
- Linear Operators



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Example:



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Brute Force:

- For each position in S:
 - Test if the next |T| letters in S match those in T

$$S=ACDBEFCDBE$$
 $T=CDB$
 $CDBBBBBBBBB$
 $O(|S|*|T|)$



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Brute Force:

- For each position in S:
 - Test if the next |T| letters in S match those in T

Can we do this more efficiently?



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Observation:

On a failed match, we don't have to compare all |T| letters in T:

S=ACDBEFCDBE COBBCOBBB

T=CDB

Comparisons: 3



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Observation:

What if the situation is more complex?

S=AAAAAAAAAAAAB AA**ABBBBBB**B

T=AAAB

Comparisons: 4



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Knuth et al. (1977):

On a failed match, we don't have to re-start the matching.



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Knuth et al. (1977):

On a failed match, we don't have to re-start the matching.

The key is to know where in *T* we have to start comparing.



Challenge:

Given strings S and T, find all occurrences of T as a substring of S.

Knuth et al. (1977):

The size of the shift on a mismatch is determined by the repetitions in T, is independent of S, and can be computed in O(|T|) time.

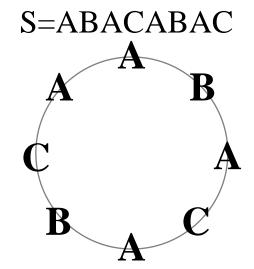
For more details, see:

Fast Pattern Matching in Strings.



Applications:

If we think of a string as a signal on a circle:

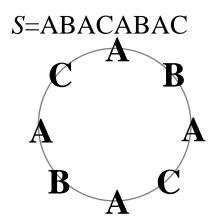


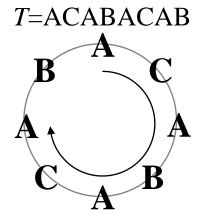


Applications:

If we think of a string as a signal on a circle:

We can test if signal T is a rotation of S
 by testing if T is a substring of SS





SS=ABACAB ACABACAB AC T= ACABACAB

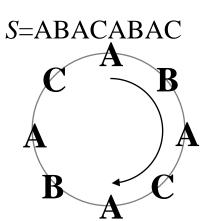


Applications:

If we think of a string as a signal on a circle:

- We can test if signal T is a rotation of S by testing if T is a substring of SS
- We can test if S has rotational symmetry by testing if S is a substring of SS







Applications:

If we think of a string as a signal on a circle:

- We can test if signal T is a rotation of S by testing if T is a substring of SS:
- We can test if S has rotational symmetry by testing if S is a substring of SS.
- We can test if S has reflective symmetry
 by testing if S is a substring of (SS)^t S=ABACABAC

B A C



Advantages:

 A fast (linear time) algorithm for performing pattern detection on discrete signals.

<u>Disadvantages</u>:

- Can only tell us if there is a perfect match
 - We need a continuous measure of similarity for real-world data
- Only works for signals on a circle (or a line)
 - Hard to generalize to signals on more complex / interesting domains

Outline



Fast Substring Matching

Math Review

- Complex Numbers
- Vector Spaces
- Linear Operators



 A complex number c is any number that can be written as:

$$c = a + ib$$

where a and b are real numbers and i is the square root of -1:

$$i^2 = -1$$



Given two complex numbers, $c_1=a_1+ib_1$ and $c_2=a_2+ib_2$:

The sum of the numbers is:

$$c_1 + c_2 = (a_1 + a_2) + i(b_1 + b_2)$$



Given two complex numbers, $c_1=a_1+ib_1$ and $c_2=a_2+ib_2$:

The sum of the numbers is:

$$c_1 + c_2 = (a_1 + a_2) + i(b_1 + b_2)$$

• The product of the numbers is:

$$c_1c_2 = (a_1 + ib_1)(a_2 + ib_2)$$

$$= a_1a_2 + ib_1ib_2 + a_1ib_2 + ib_1a_2$$

$$= (a_1a_2 - b_1b_2) + i(a_1b_2 + b_1a_2)$$



Given a complex numbers, c=a+ib:

The negation of the number is:

$$-c = -a - ib$$



Given a complex numbers, c=a+ib:

The negation of the number is:

$$-c = -a - ib$$

The conjugate of the number is:

$$\bar{c} = a - ib$$



Given a complex numbers, c=a+ib:

The negation of the number is:

$$-c = -a - ib$$

The conjugate of the number is:

$$\overline{c} = a - ib$$

The reciprocal of the number is:

$$\frac{1}{c} = \frac{1}{c} \frac{\overline{c}}{\overline{c}} = \left(\frac{a}{a^2 + b^2}\right) - i\left(\frac{b}{a^2 + b^2}\right)$$



Why do we care?



Why do we care?

Fundamental Theorem of Algebra

Given any polynomial:

$$p(x) = a_0 + a_1 x + a_2 x^2 + \dots + a_n x^n$$

there always exists a complex number c_0 s.t.:

$$p(c_0) = 0$$

Vector Spaces



A (real/complex) vector space V is a <u>set</u> of elements $v \in V$, with:

- An <u>addition</u> operator "+", and
- A <u>scaling</u> operator "."

(i.e. we can add any two vectors together to get a vector and if we scale a vector by a number we also get a vector.)

Vector Spaces (Formal Properties 1)



For all u, v, and w in V:

Associative Addition:

$$(U+V)+W=U+(V+W)$$

Commutative Addition:

$$U+V=V+U$$

Additive Identity:

There exists a unique vector 0 in *V* such that:

$$u+0=u$$

Additive Inverse:

There exists a vector (-u) in V such that:

$$u+(-u)=0$$

Vector Spaces (Formal Properties 2)

2

For all *u*, and *v* in *V*, and all (real / complex) scalars *a* and *b*:

Distributive over vector addition:

$$a(u+v) = (au) + (av)$$

Distributive over scalar addition:

$$(a+b)u=(au)+(bu)$$

Compatible scalar multiplication:

$$a(bu) = (ab)u$$

Scalar Identity:

Vector Spaces: Examples



Real Vector Spaces:

- The real / complex numbers
- The space of *n*-dimensional arrays with real / complex entries
- The space of mxn matrices with real / complex entries
- The space of real / complex valued functions on a circle / line / plane / sphere / etc.

Complex Vector Spaces:

- The complex numbers
- The space of n-dimensional arrays with complex entries
- The space of mxn matrices with complex entries
- The space of complex valued functions on a circle / line / plane / sphere / etc.



A basis of V is a finite set $\{v_1, ..., v_n\}$ of vectors such that:

1. Any vector *v* in *V* can be expressed as:

$$v = a_1 v_1 + \dots + a_n v_n$$

where the a_i are (real / complex) scalars.

2. No basis vector v_i can be expressed as the linear sum of the other basis vectors.



Many different bases can be used to represent the same vector space.

Example:

Consider the set of points in 2D Euclidean space.

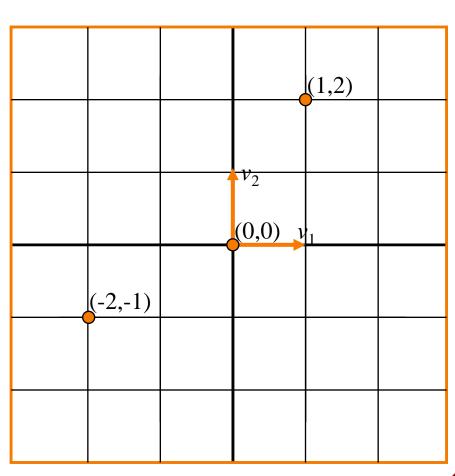


Many different bases can be used to represent the same vector space.

Example:

Consider the set of points in 2D Euclidean space.

We can represent each vector in terms of its (x,y)-coordinates.



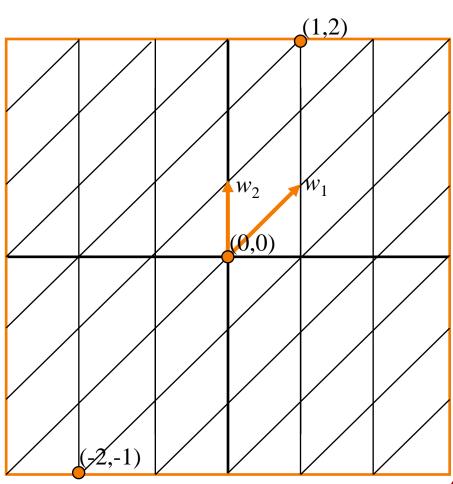


Many different bases can be used to represent the same vector space.

Example:

Consider the set of points in 2D Euclidean space.

Or we could use a different basis...



Linear Maps



A function $L: V \rightarrow W$, is a <u>linear map</u> if for all v_1 and v_2 in V and all (real / complex) scalars a and b:

$$L(av_1 + bv_2) = a \cdot L(v_1) + b \cdot L(v_2)$$

Linear Maps



A function $L: V \rightarrow W$, is a <u>linear map</u> if for all v_1 and v_2 in V and all (real / complex) scalars a and b:

$$L(av_1 + bv_2) = a \cdot L(v_1) + b \cdot L(v_2)$$

If it exists, the inverse of a linear map L is the map L^{-1} with the property that:

$$L^{-1}$$
 $(v) = v$

Linear Maps



If $L: V \rightarrow W$, is a linear map:

The set of vectors:

$$K = \forall \in V \mid L(v) = 0$$

is a vector subspace called the kernel.

The set of vectors:

$$I = \forall \in W \mid \exists v \in V \text{ s.t. } L(v) = w$$

is a vector subspace called the image.

Matrices



$$L(v) = b_1 v_1 + \dots + b_n v_n$$

with:

$$\begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix} = \begin{pmatrix} M_{11} \cdots M_{1n} \\ \vdots & \ddots & \vdots \\ M_{n1} \cdots M_{nn} \end{pmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$$



Given a vector space V, and given two bases $\{v_1, ..., v_n\}$ and $\{w_1, ..., w_n\}$, then since $\{v_1, ..., v_n\}$ is a basis, there exist values B_{ii} such that:

$$w_{1} = B_{11}v_{1} + \dots + B_{1n}v_{n}$$

$$\vdots$$

$$w_{n} = B_{n1}v_{1} + \dots + B_{nn}v_{n}$$



Given a vector space V, and given two bases $\{v_1,\ldots,v_n\}$ and $\{w_1,\ldots,w_n\}$, the matrix B is the change of basis matrix.

If ν is any vector in V, we can write out ν in terms of the basis $\{v_1,\ldots,v_n\}$ as $v=a_1v_1+\ldots+a_nv_n$.

We can also write out v in terms of the basis $\{W_1,...,W_n\}$ as $v=b_1W_1+...+b_nW_n$.

The coefficients are related by:

Its are related by:
$$\begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix} = \begin{pmatrix} B_{11} \cdots B_{1n} \\ \vdots & \ddots & \vdots \\ B_{n1} \cdots B_{nn} \end{pmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$$



Given:

- A vector space V,
- Two bases $\{v_1, \dots, v_n\}$ and $\{w_1, \dots, w_n\}$,
- A linear operator L represented by the matrix M in terms of the basis $\{v_1, ..., v_n\}$.

The matrix representation for L in terms of the basis $\{w_1, ..., w_n\}$ is given by:

 BMB^{-1}



Why do we care?



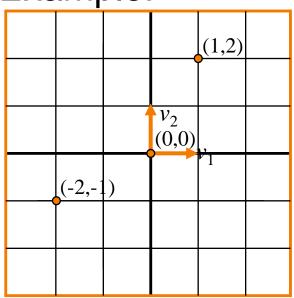
Why do we care?

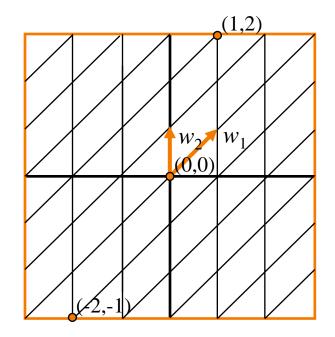
Choosing the appropriate basis can make it much easier to understand a linear operator.



Why do we care?

Example:





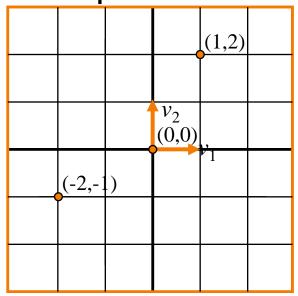
$$B = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}$$

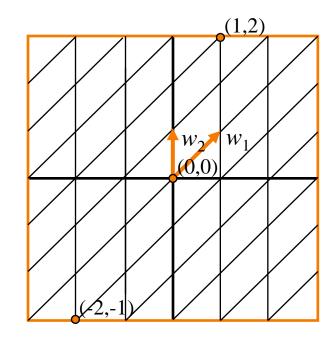
$$B^{-1} = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$



Why do we care?

Example:





$$B = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}$$

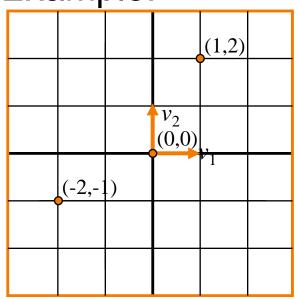
$$B^{-1} = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$

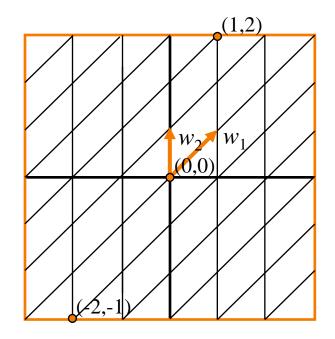
$$M = \begin{pmatrix} 2 & 0 \\ -1 & 1 \end{pmatrix} \implies BMB^{-1}$$



Why do we care?

Example:





$$B = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}$$

$$B^{-1} = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$

$$M = \begin{pmatrix} 2 & 0 \\ -1 & 1 \end{pmatrix} \longrightarrow$$

$$M = \begin{pmatrix} 2 & 0 \\ -1 & 1 \end{pmatrix} \implies BMB^{-1} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 2 & 0 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix} = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}$$

Determinants



The determinant is a function that associates a scalar value to every square (nxn) matrix.

One way to think about this is to write out the matrix as a set of column vectors:

$$M = \langle w_1 | \cdots | w_n \rangle$$

Then the determinant of M is the (signed) volume of the parallelepiped with sides $\{w_1, \ldots, w_n\}$

Determinants



The determinant of a matrix M is equal to zero if and only if there exists a vector v in V, with $v\neq 0$, such that M(v)=0.

Eigenvalues and Eigenvectors



The scalar λ is an <u>eigenvalue</u> of a matrix M if there exists a vector v in V such that:

$$\lambda v = M(v)$$

In this case, *v* is an <u>eigenvector</u> of *M*.

Eigenvalues and Eigenvectors



If M has an eigenvector v with eigenvalue λ , this must mean that:

$$0 = (M - \lambda)(v)$$

Thus, the matrix:

$$M - \lambda \cdot \text{Id} = \begin{pmatrix} M_{11} - \lambda \end{pmatrix} & \cdots & M_{1n} \\ \vdots & \ddots & \vdots \\ M_{n1} & \cdots & M_{nn} - \lambda \end{pmatrix}$$

must have zero determinant.

Characteristic Polynomials



If we treat λ as a variable, then the determinant: $\det(M - \lambda \cdot \mathrm{Id})$

is a polynomial of degree n in λ . This polynomial is the <u>characteristic polynomial</u> of M.

Characteristic Polynomials



The roots of the characteristic polynomial of M: $\det(M - \lambda \cdot \operatorname{Id})$ are precisely the eigenvalues of the matrix M.

Thus, if we are considering *M* as a matrix acting on a complex vector space, *M* must always have at least one eigenvalue.