

Robustness

Outline

- 1 Introduction
 - (Simplified) history
 - Robustness: Two main issues
- 2 Arithmetic issues
 - Reminder: floating-point arithmetic
 - Consequences
 - Exact Geometric Computing
- 3 Degenerate cases

Introduction

1 Introduction

- (Simplified) history
- Robustness: Two main issues

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Introduction — (Simplified) history

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Early algorithms [70's]

- Incremental
- Gift wrapping

non-optimal

“simple”

actually coded

motivated by applications (meshes, reconstruction)

Optimal algorithms [80's]

- Divide & conquer
- Plane sweep

worst-case optimal

simple

~~actually coded~~

~~motivated by applications (meshes, reconstruction)~~

computational geometry known as a **purely theoretical** field

A more pragmatic point of view

Randomized algorithms [90's]

- Delaunay tree
- Conflict graph
- History graph
- Delaunay hierarchy
- Spatial sorting (BRIO)

non-optimal
“simple”

A more pragmatic point of view

Randomized algorithms [90's]

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Software development

- VRONI
- TRIANGLE
- LEDA
- CGAL

A more pragmatic point of view

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→ Robustness issues [95's]

Introduction — Robustness: Two main issues

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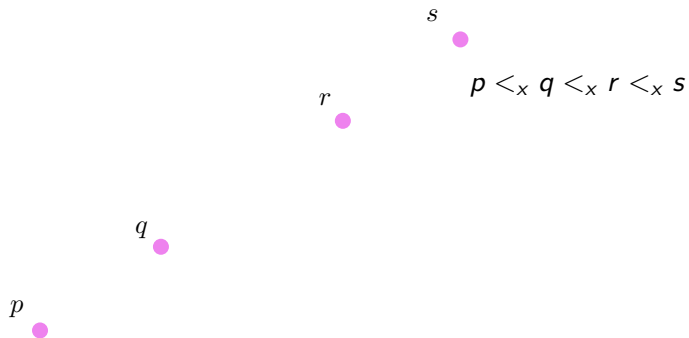
- Arithmetic issues
- Degenerate cases

Arithmetic issues

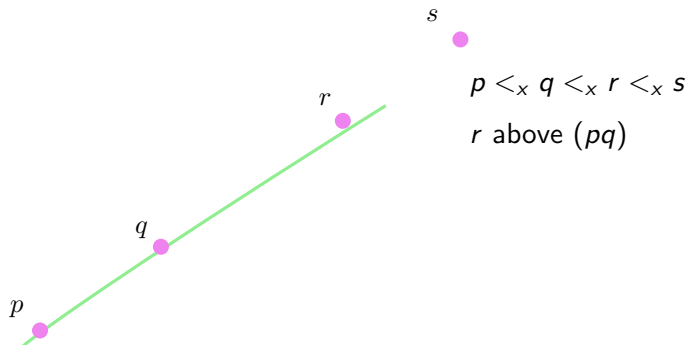
- Algorithms designed in [Real RAM model](#)
- `float`, `double` are not reals

Rounding errors

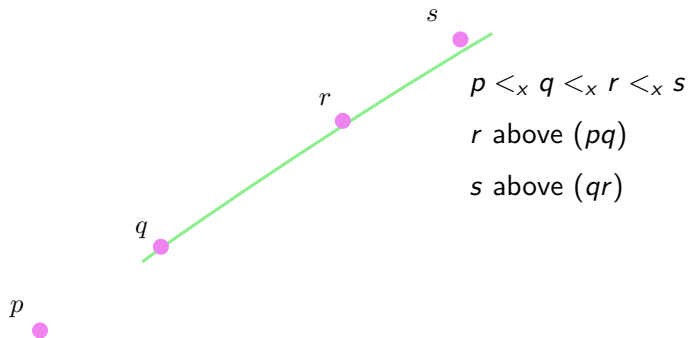
Arithmetic issues



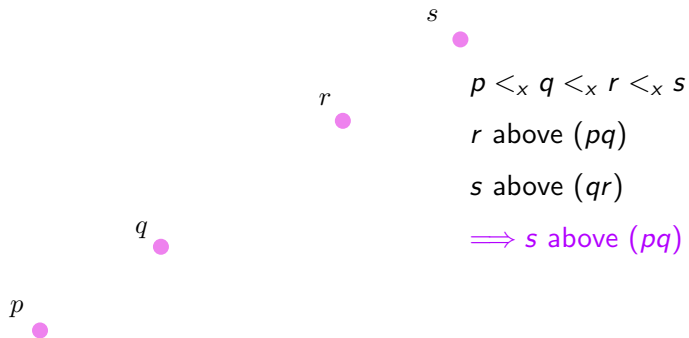
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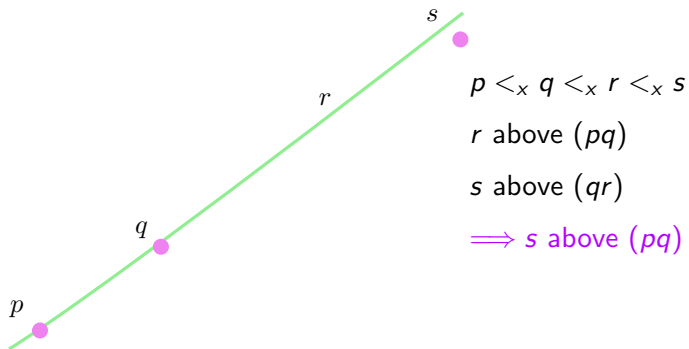
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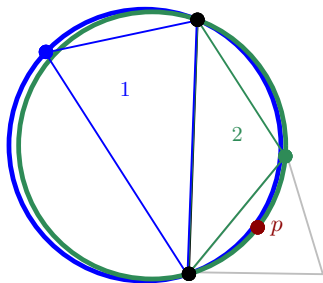


Arithmetic issues



\implies inconsistency

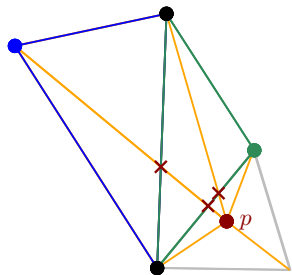
Arithmetic issues



$\text{in_disk}_1(p) = \text{true}$

$\text{in_disk}_2(p) = \text{false}$

Arithmetic issues



$\text{in_disk}_1(p) = \text{true}$

$\text{in_disk}_2(p) = \text{false}$

inconsistencies!
algorithm fails

Arithmetic issues

- Algorithms designed in **Real RAM model**
- **float, double** are not reals

Rounding errors

⇒ **inconsistencies**

not just imprecisions

⇒ failure

see course **convex hull**

Convex hull

Rounding errors possible

Orientation predicate

$$p = \left(\frac{1}{2} + x.u, \frac{1}{2} + y.u\right)$$

$$0 \leq x, y \leq 256, u = 2^{-53}$$

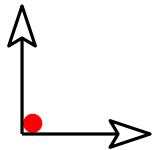
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$$r = (24, 24)$$

Teaser robustness lecture

orientation(p, q, r)

evaluated with double



Convex hull

Rounding errors possible

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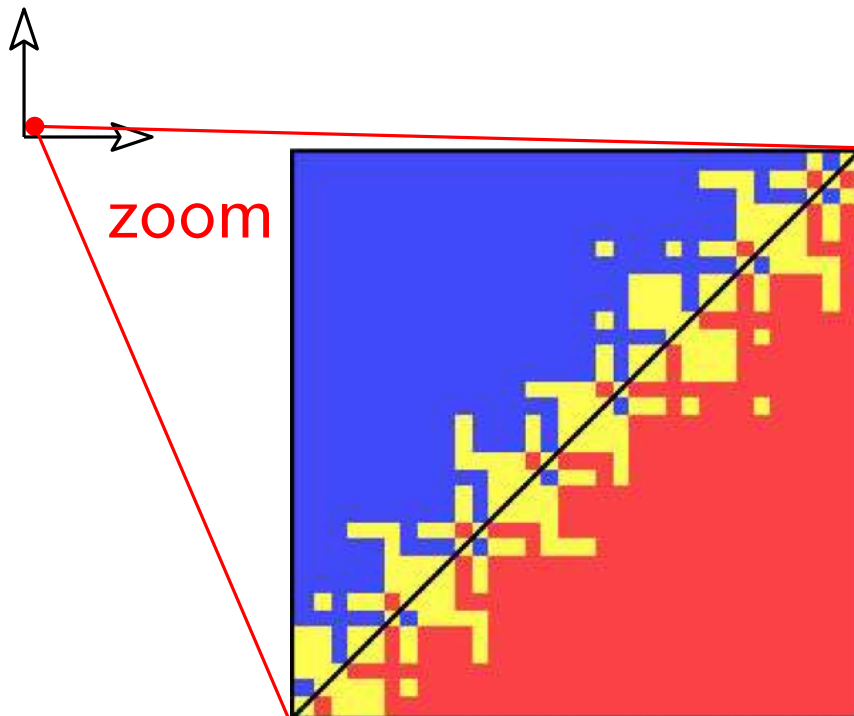
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evaluated with double

≤ 0

0

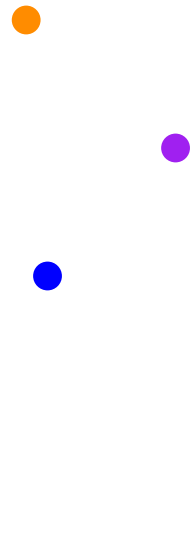
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Convex hull

Teaser robustness lecture

Buggy degenerate example
(single precision)



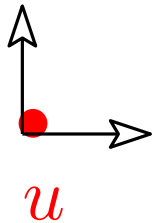
$$w_1 = (12, 12)$$

$$w_2 = (24, 24)$$

$$w_3 = (30, 30.000001)$$

$$w_4 = (23, 36)$$

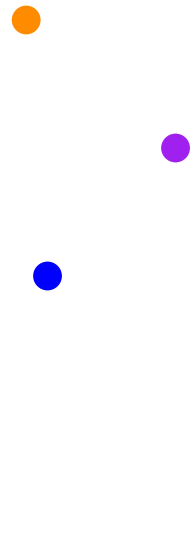
$$w_5 = (0.5000029, 0.5000027)$$



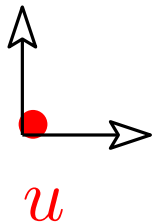
Convex hull

Teaser robustness lecture

Buggy degenerate example
(single precision)



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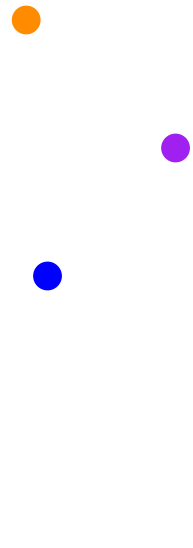
Input : point set S
 $u = v =$ lowest point in S ;

Jarvis

Convex hull

Teaser robustness lecture

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Do

$n = \text{first in } S;$

For each $w \in S$

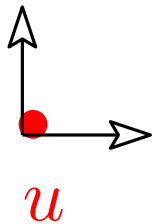
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$S = S \setminus \{v\}$

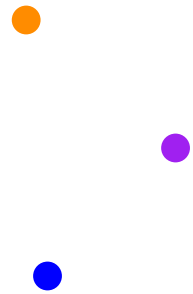
While $v \neq u$



Convex hull

Teaser robustness lecture

Buggy degenerate example
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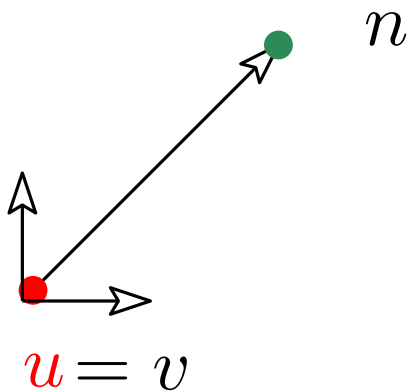
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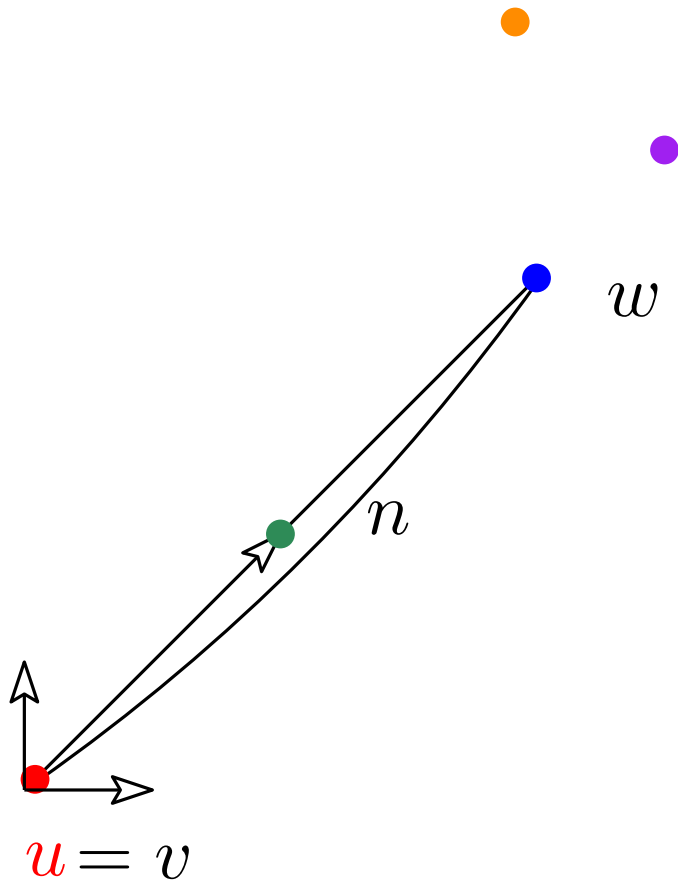
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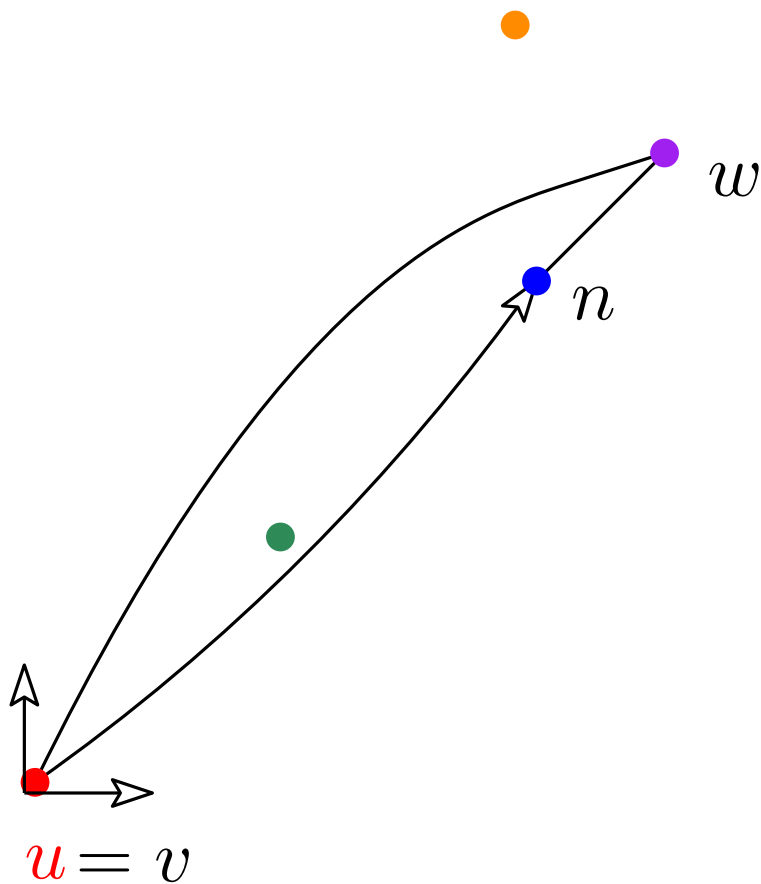
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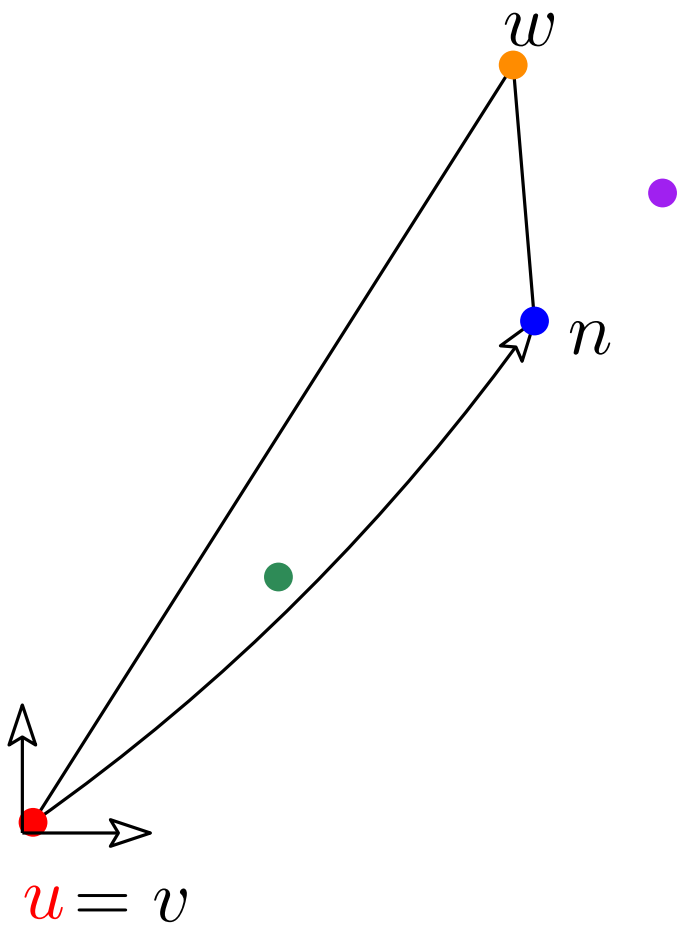
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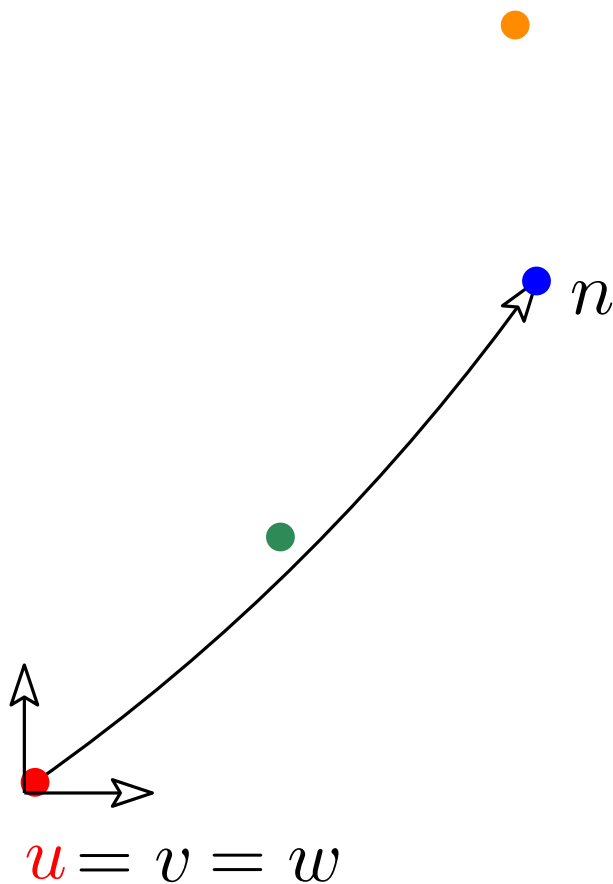
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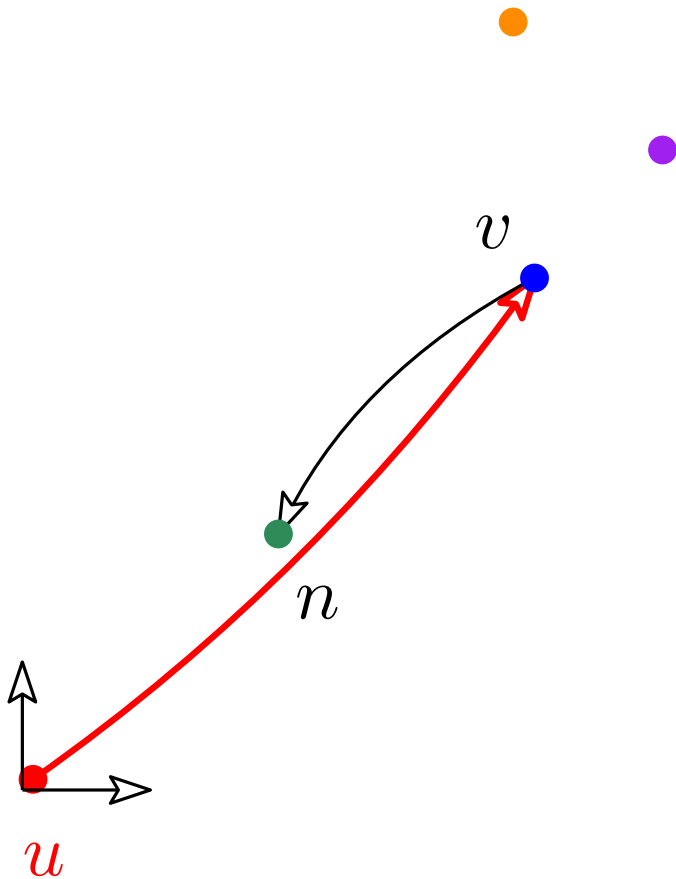
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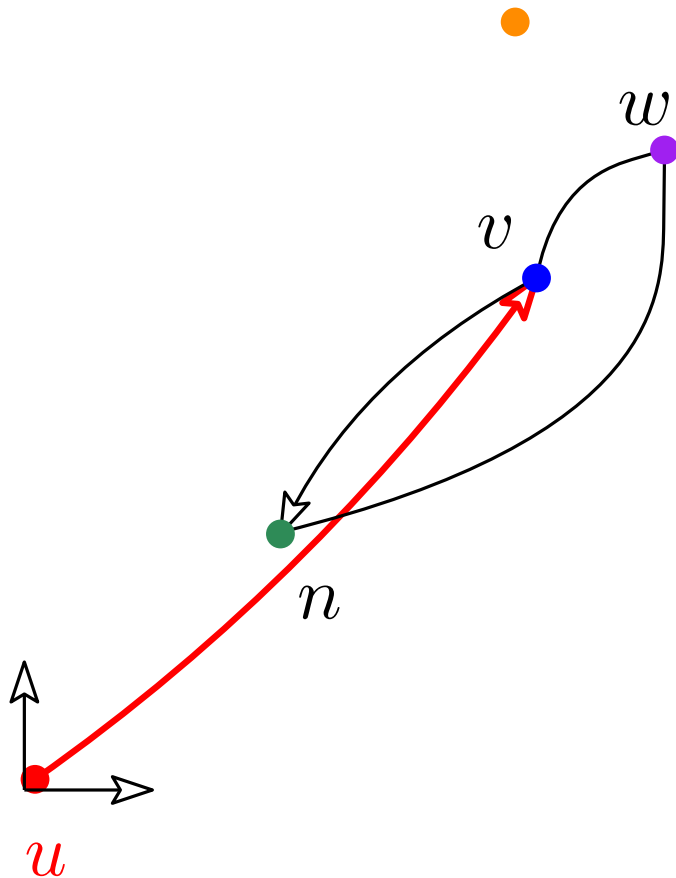
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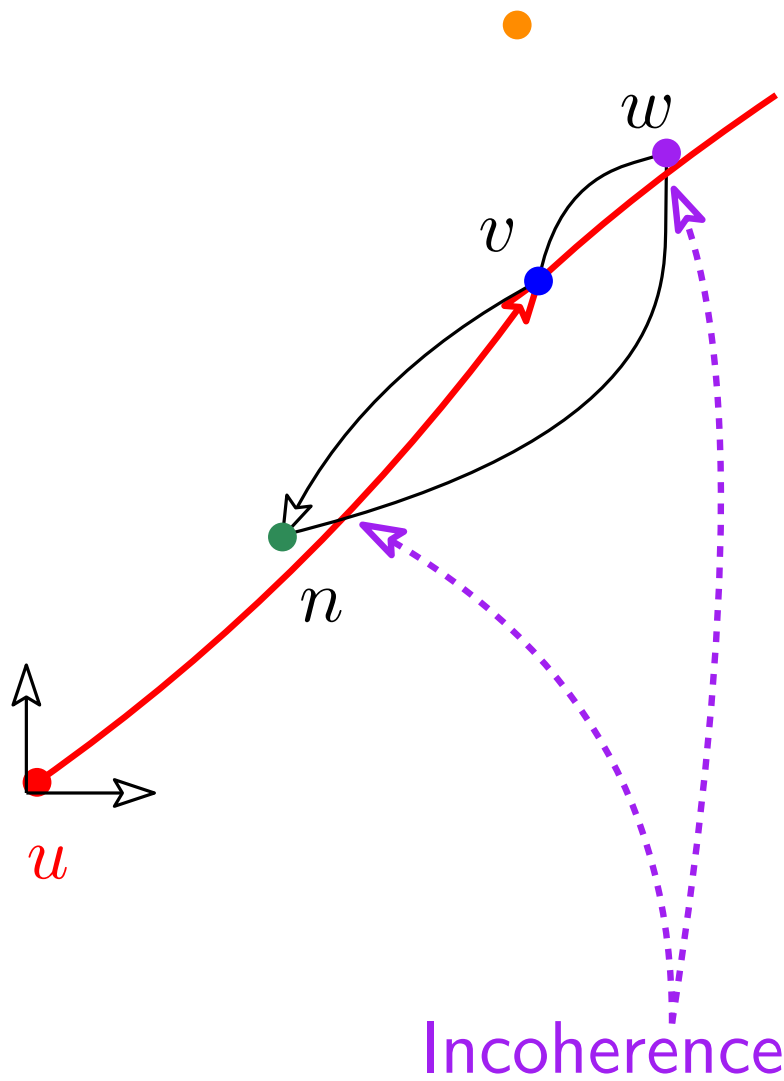
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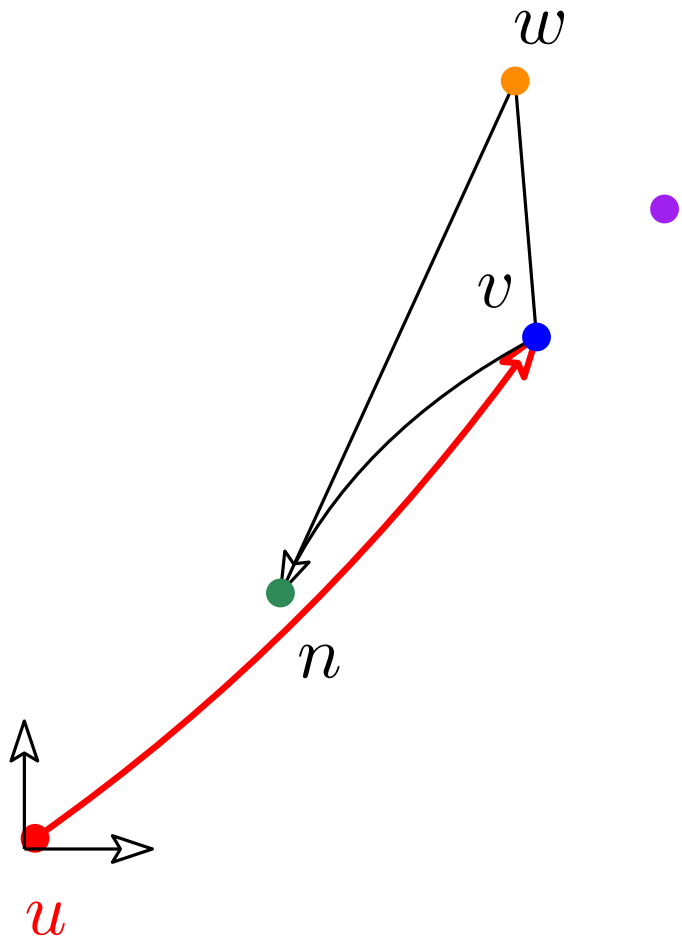
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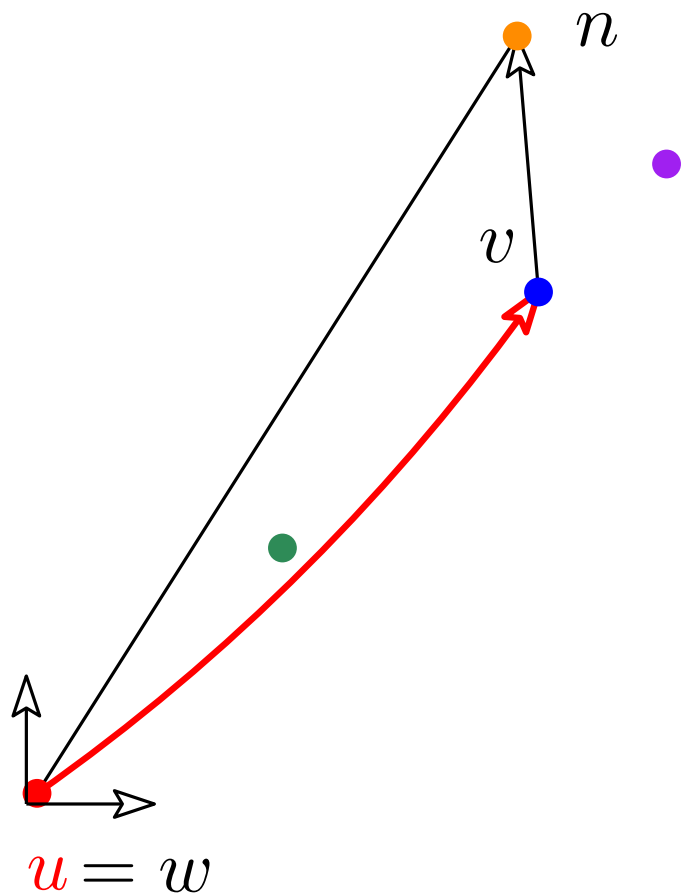
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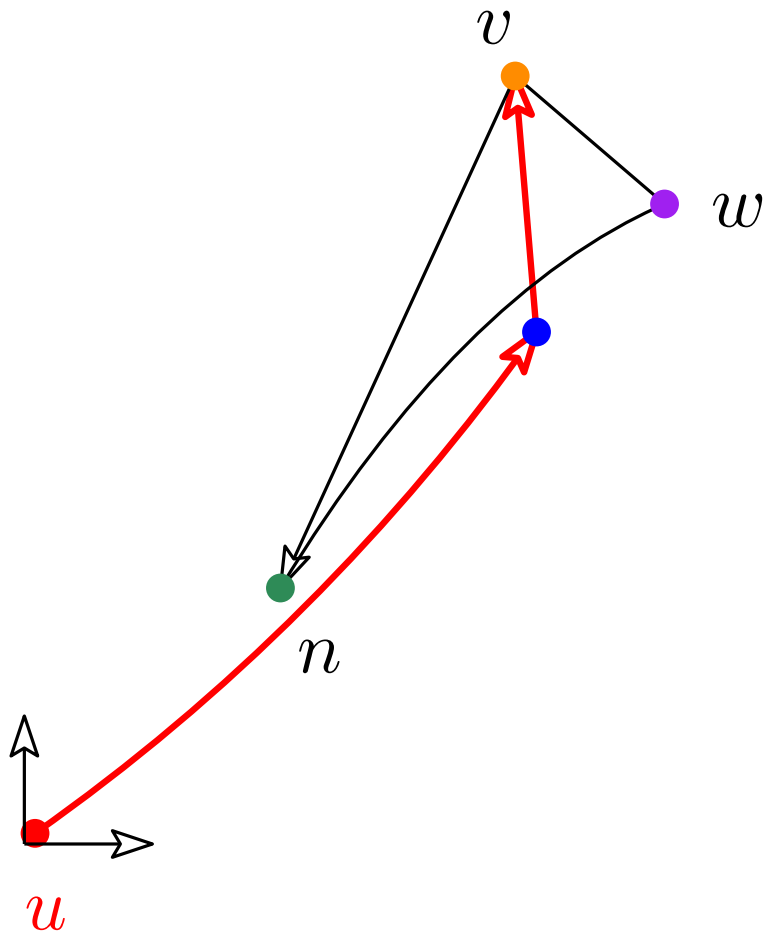
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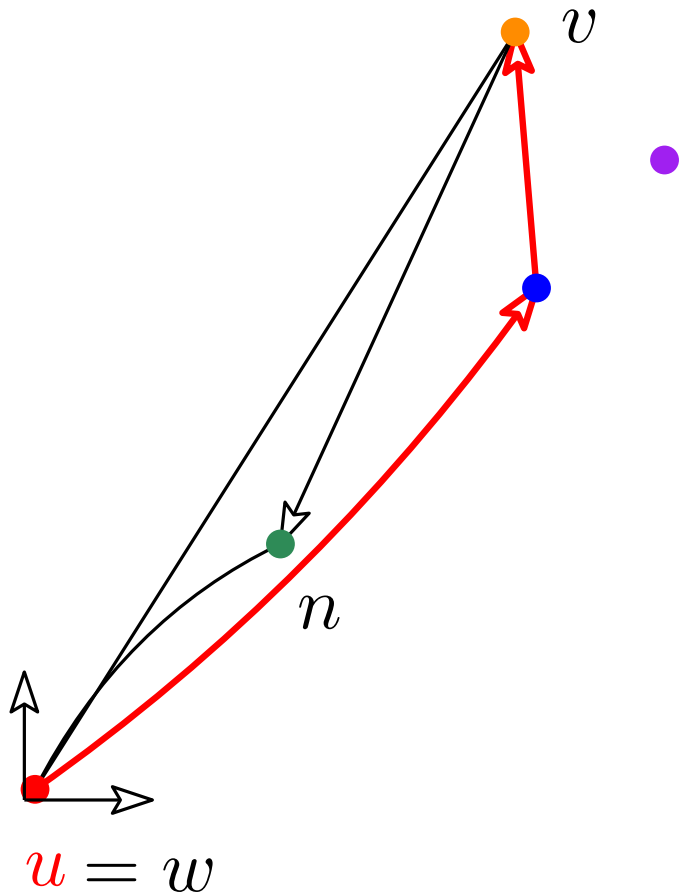
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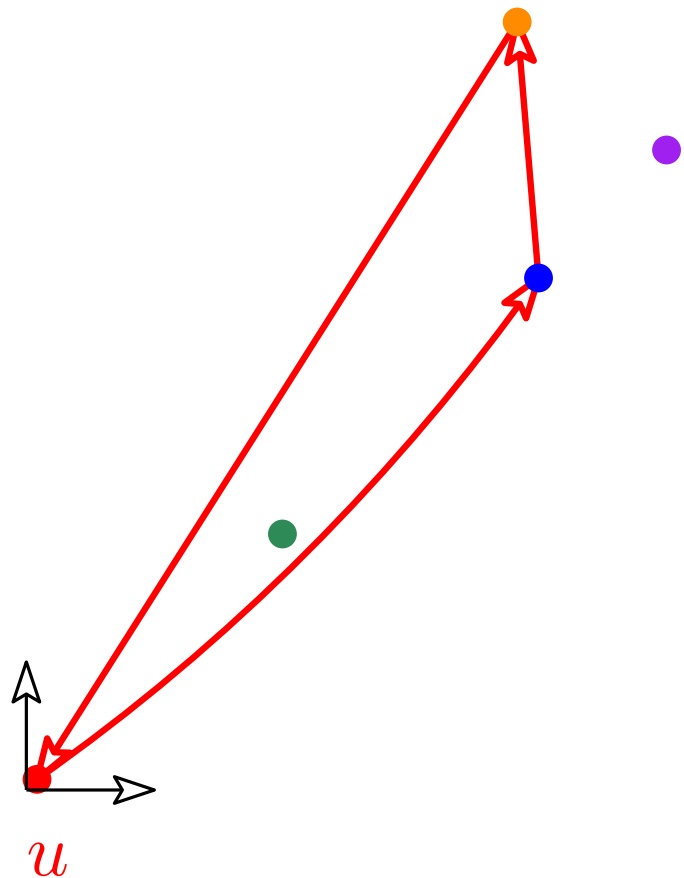
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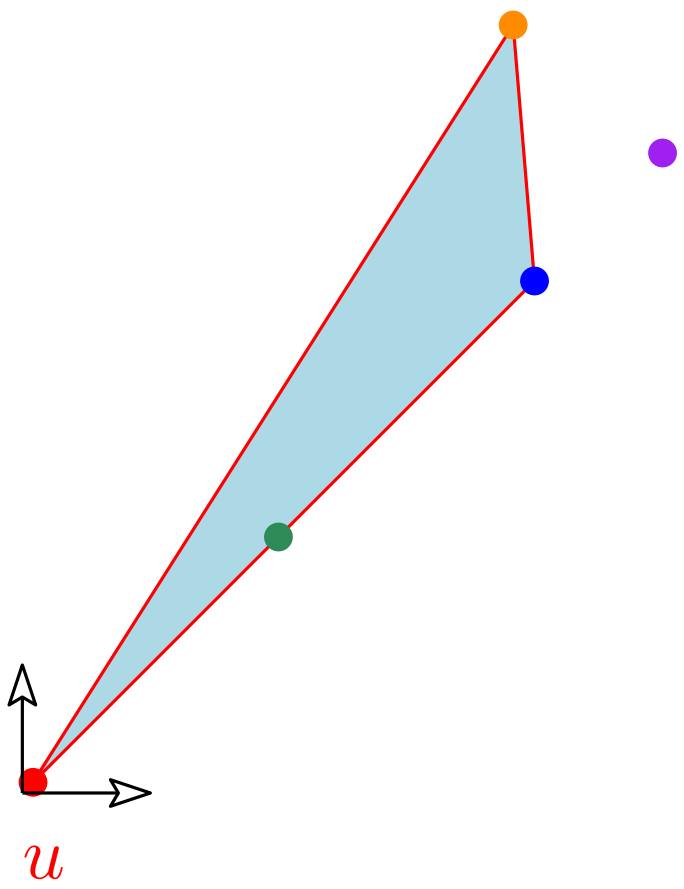
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Convex hull

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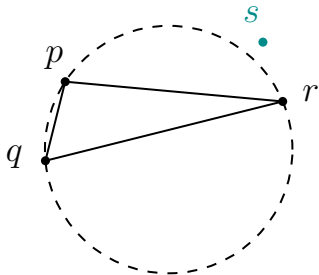
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Result is really wrong

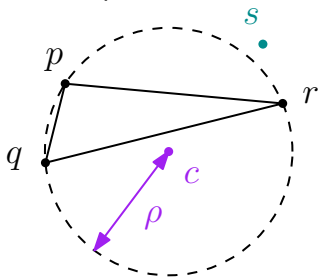
Arithmetic issues

in_disk predicate



Arithmetic issues

in_disk predicate



circle \mathcal{C} through p, q, r

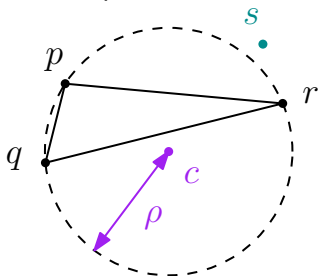
unknowns c, ρ

solve \rightarrow

- center c
- radius ρ

Arithmetic issues

in_disk predicate



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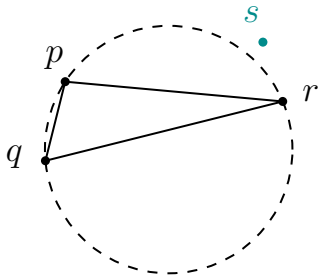
Bad idea...

rounding errors $\leftrightarrow p, q, r \notin \mathcal{C}(c, \rho)$

“random” result for s

Arithmetic issues

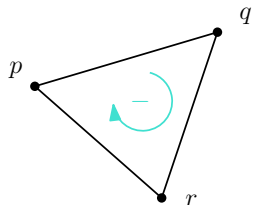
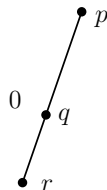
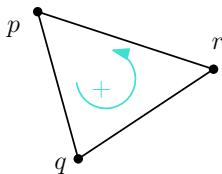
in_disk predicate



$$\text{in_disk}(p, q, r, s) = \text{sign} \begin{vmatrix} 1 & 1 & 1 & 1 \\ p_x & q_x & r_x & s_x \\ p_y & q_y & r_y & s_y \\ p_x^2 + p_y^2 & q_x^2 + q_y^2 & r_x^2 + r_y^2 & s_x^2 + s_y^2 \end{vmatrix}$$

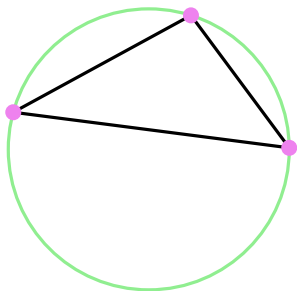
Arithmetic issues

orientation predicate



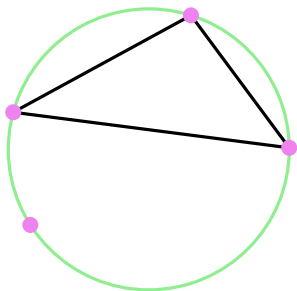
$$\text{orient}(p, q, r) = \text{sign} \begin{vmatrix} 1 & 1 & 1 \\ p_x & q_x & r_x \\ p_y & q_y & r_y \end{vmatrix}$$

Degenerate cases



Choices

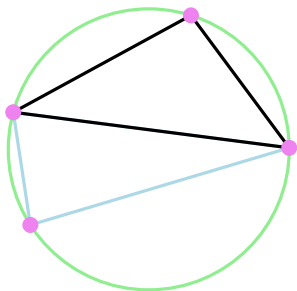
Degenerate cases



Choices

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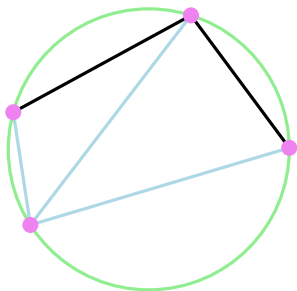
Degenerate cases



Choices

? new point “outside disk”

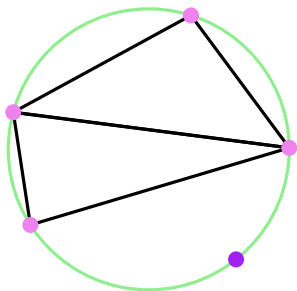
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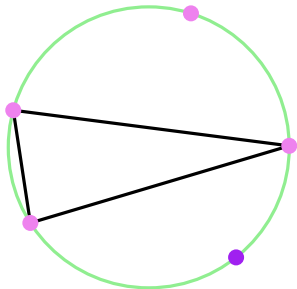
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Degenerate cases



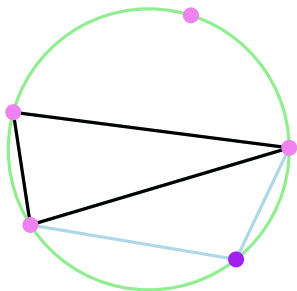
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Degenerate cases



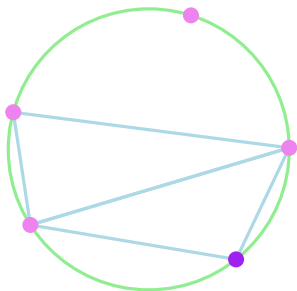
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Degenerate cases



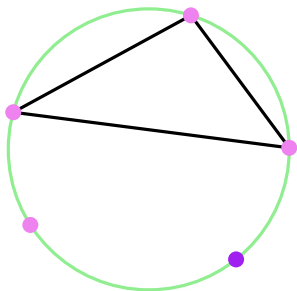
choice: new point “outside”

Degenerate cases



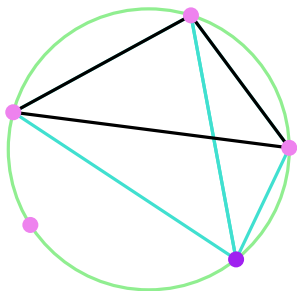
choice: new point “outside”

Degenerate cases



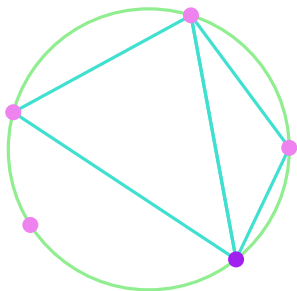
?

Degenerate cases



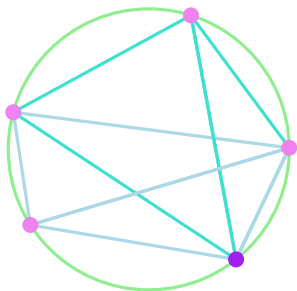
choice: new point “inside”

Degenerate cases



choice: new point “inside”

Degenerate cases



inconsistency

decisions must be made
in a consistent way

Arithmetic issues

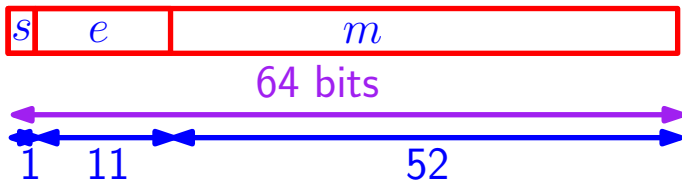
- 1 Introduction
 - (Simplified) history
 - Robustness: Two main issues
- 2 Arithmetic issues
 - Reminder: floating-point arithmetic
 - Consequences
 - Exact Geometric Computing
- 3 Degenerate cases

Arithmetic issues — Reminder: floating-point arithmetic

- 1 Introduction
 - (Simplified) history
 - Robustness: Two main issues
- 2 Arithmetic issues
 - **Reminder: floating-point arithmetic**
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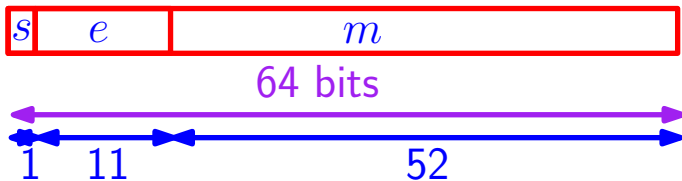
double

IEEE 754



double

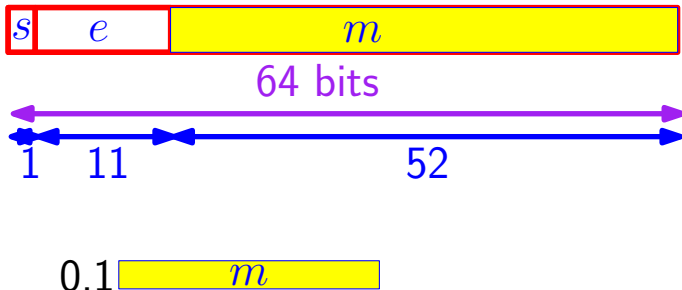
IEEE 754



0.1

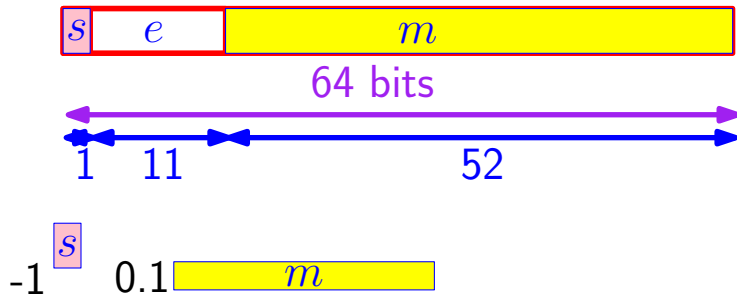
double

IEEE 754



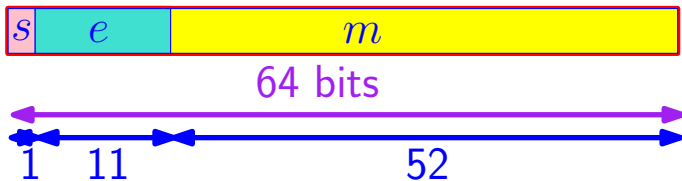
double

IEEE 754



double

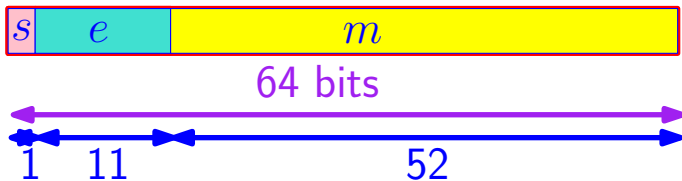
IEEE 754



$$-1^s \cdot 0.1 \cdot m \cdot 2^{-1024+e}$$

double

IEEE 754



$$-1^s \cdot 0.1 \overbrace{m} \cdot 2^{-1024+e}$$

normalized numbers

Representable Numbers



Representable Numbers



$$0.11010\dots 01001 \times 2^{e'}$$

Representable Numbers

$$0.11010\dots 01010 \times 2^{e'}$$



$$0.11010\dots 01001 \times 2^{e'}$$

Representable Numbers

$$0.11010\dots 01010 \times 2^{e'}$$

$$0.11010\dots 01011 \times 2^{e'}$$



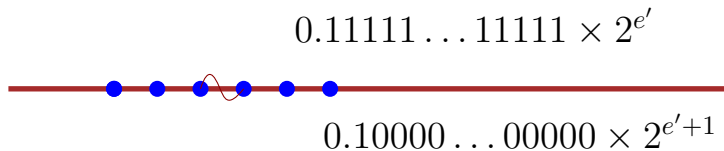
$$0.11010\dots 01001 \times 2^{e'}$$

Representable Numbers

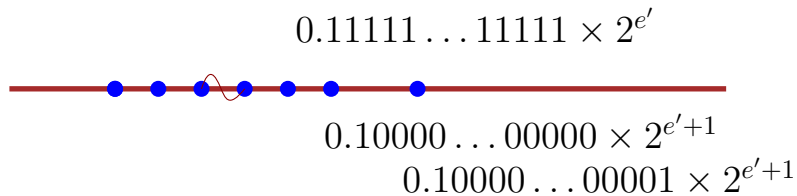
$$0.11111 \dots 11111 \times 2^{e'}$$



Representable Numbers



Representable Numbers



Representable Numbers

$$0.11111 \dots 11111 \times 2^{e'}$$



$$0.10000 \dots 00000 \times 2^{e'+1}$$

$$0.10000 \dots 00001 \times 2^{e'+1}$$

$$0.10000 \dots 00010 \times 2^{e'+1}$$

$$0.10000 \dots 00011 \times 2^{e'+1}$$

Smallest Representable Number

$$0.00000 \dots 00000 \times 2^{-1024}$$



$$0.10000 \dots 00000 \times 2^{-1024}$$



Smallest Representable Number

$$0.00000 \dots 00000 \times 2^{-1024}$$

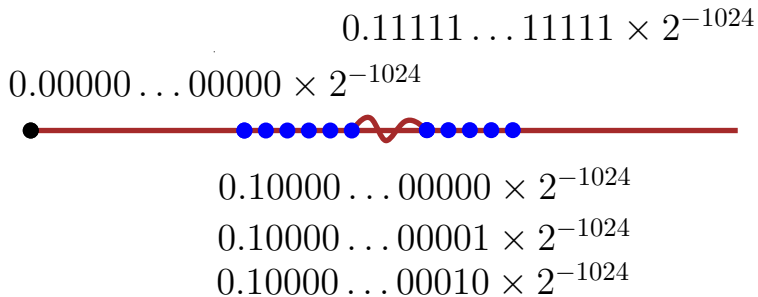


$$0.10000 \dots 00000 \times 2^{-1024}$$

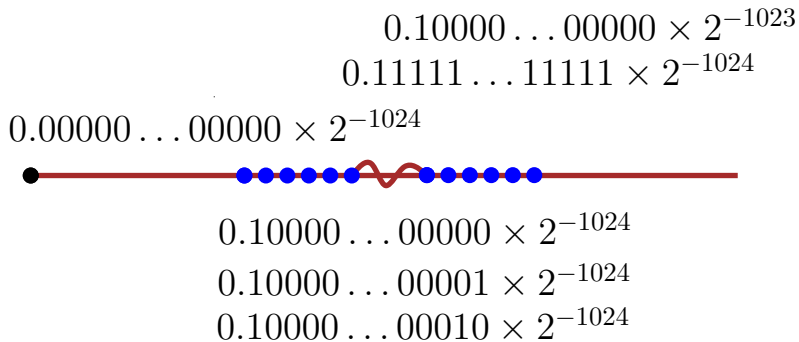
$$0.10000 \dots 00001 \times 2^{-1024}$$

$$0.10000 \dots 00010 \times 2^{-1024}$$

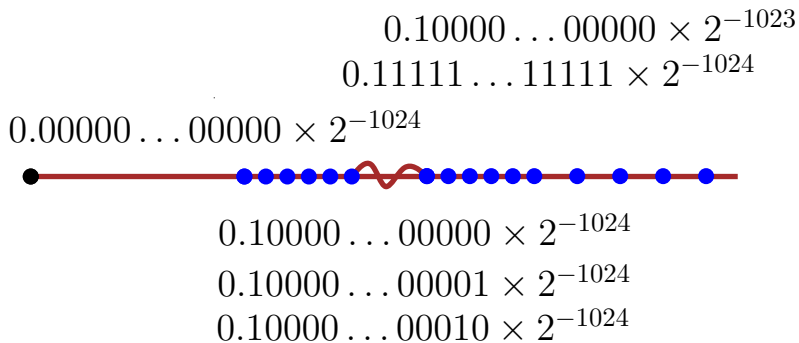
Smallest Representable Number



Smallest Representable Number



Smallest Representable Number



Denormalized Numbers

$$0.00000 \dots 00000 \times 2^{-1024}$$

$$0.10000 \dots 00000 \times 2^{-1023}$$



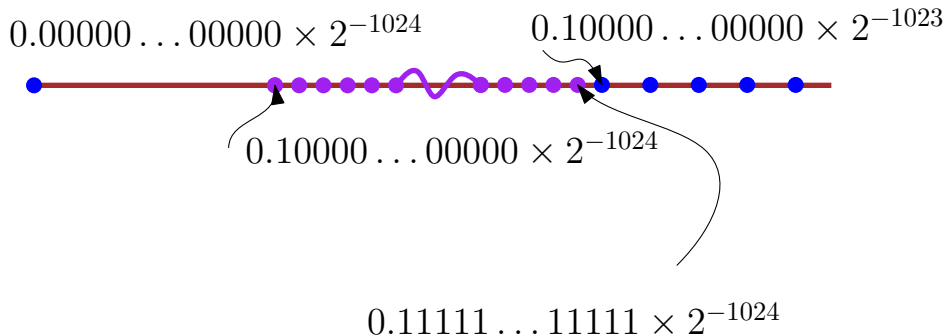
Denormalized Numbers

$$0.00000 \dots 00000 \times 2^{-1024}$$

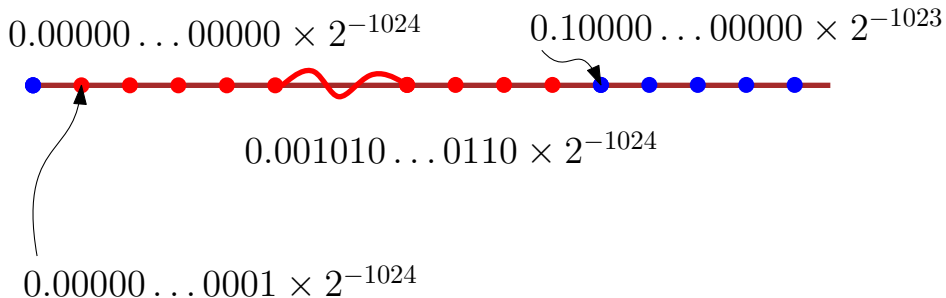
$$0.10000 \dots 00000 \times 2^{-1023}$$



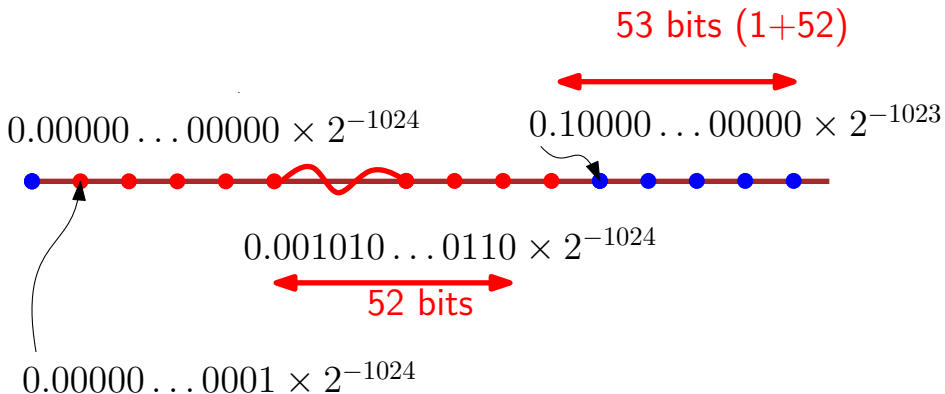
Denormalized Numbers



Denormalized Numbers

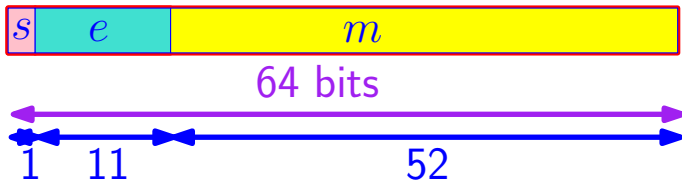


Denormalized Numbers



Denormalized Numbers

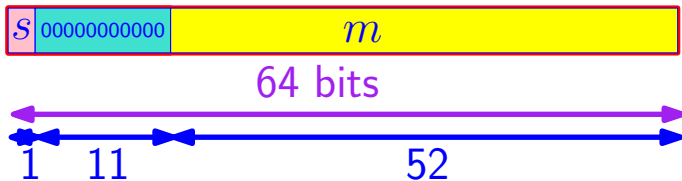
double \rightarrow normalized



$$-1^{\boxed{s}} \cdot 0.1 \boxed{m} \cdot 2^{-1024 + \boxed{e}}$$

Denormalized Numbers

double \rightarrow de-normalized

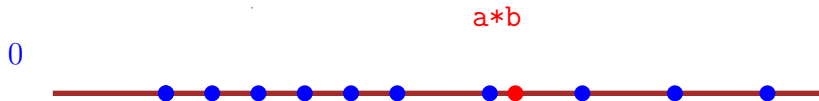


$$-1^{\boxed{S}} \cdot 0. \boxed{m} \cdot 2^{-1024}$$

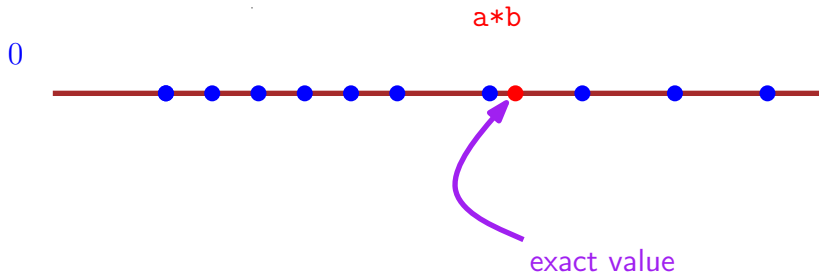
Rounding modes



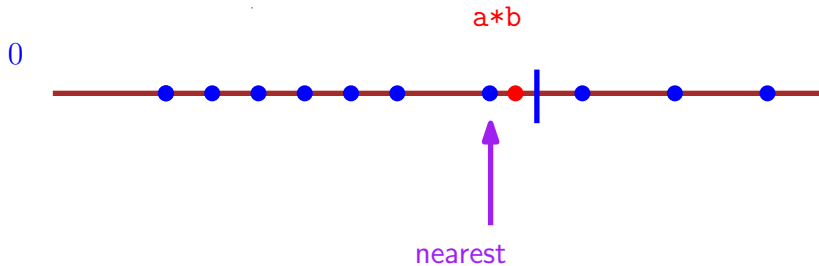
Rounding modes



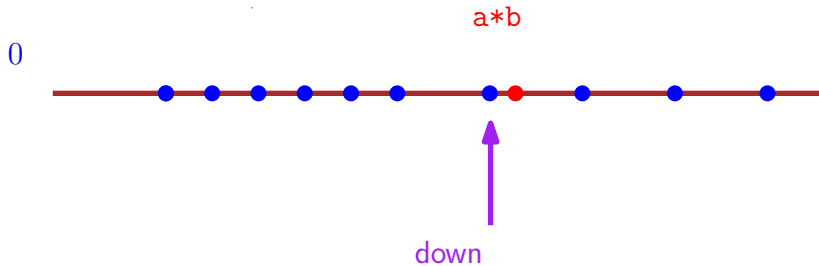
Rounding modes



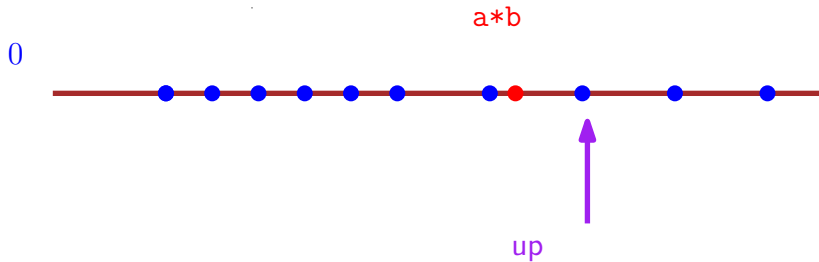
Rounding modes



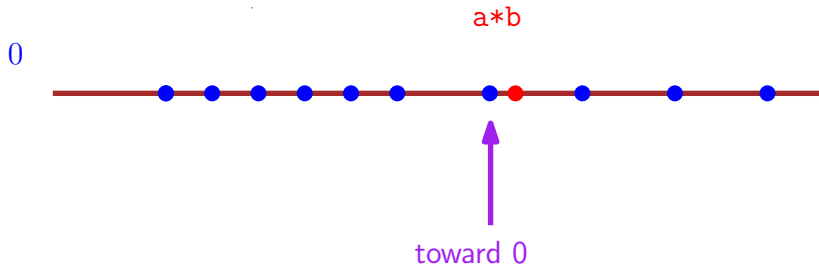
Rounding modes



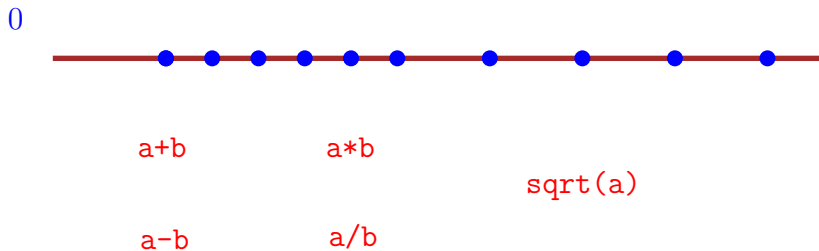
Rounding modes



Rounding modes



Rounding modes



Arithmetic issues — Consequences

1 Introduction

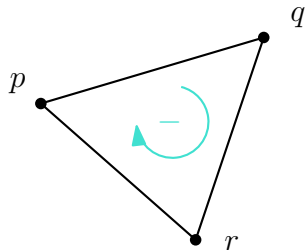
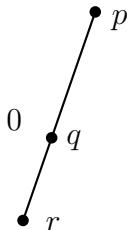
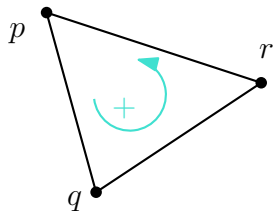
- (Simplified) history
- Robustness: Two main issues

2 Arithmetic issues

- Reminder: floating-point arithmetic
- **Consequences**
- Exact Geometric Computing

3 Degenerate cases

Orientation predicate



$$\text{sign} \begin{vmatrix} x_p & x_q & x_r \\ y_p & y_q & y_r \\ 1 & 1 & 1 \end{vmatrix} = \text{sign} \begin{vmatrix} x_q - x_p & x_r - x_p \\ y_q - y_p & y_r - y_p \end{vmatrix}$$

Toy model

double

53 binary digits

float

24 binary digits

Toy model

2 decimal digits

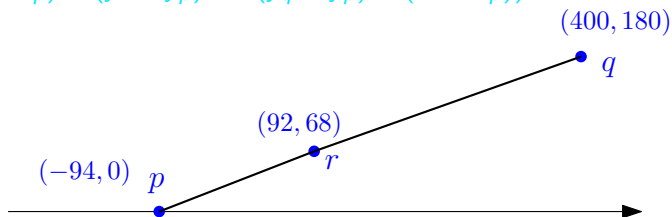
$$35 + 3.7 = 38.7 \text{ exact}$$

$$(35 + 3.3) + 0.4 \approx 38$$

$$35 + (3.3 + 0.4) \approx 39$$

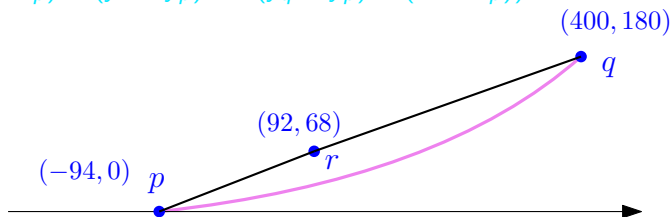
Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$



Orientation predicate in the toy model

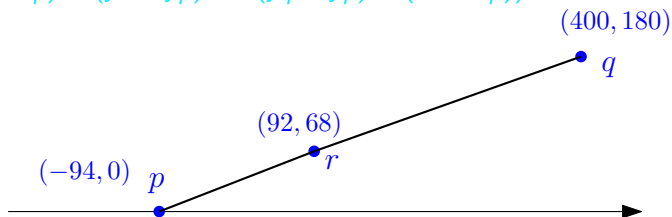
$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$



$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$

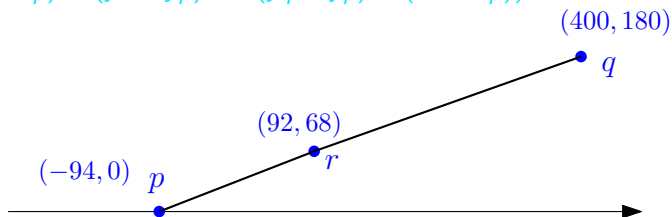


$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

$$494 \times 68 - 186 \times 180 \approx$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$



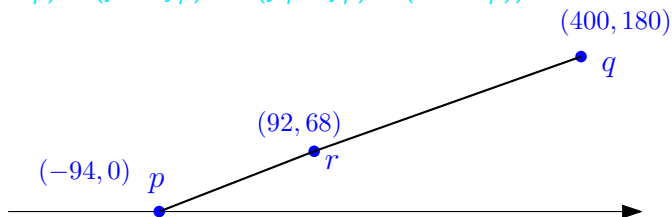
$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

$$494 \times 68 - 186 \times 180 \approx$$

$$490 \times 68 - 190 \times 180 =$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$

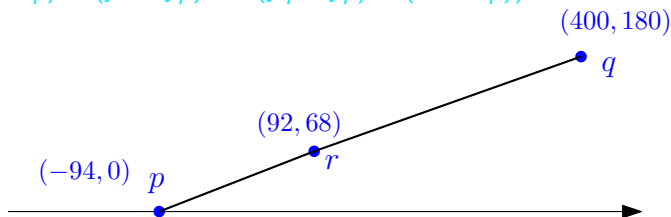


$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

$$\begin{array}{rclclcl} 494 & \times & 68 & - & 186 & \times & 180 & \approx \\ 490 & \times & 68 & - & 190 & \times & 180 & = \\ 33320 & & & - & 34200 & & & \approx \end{array}$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$

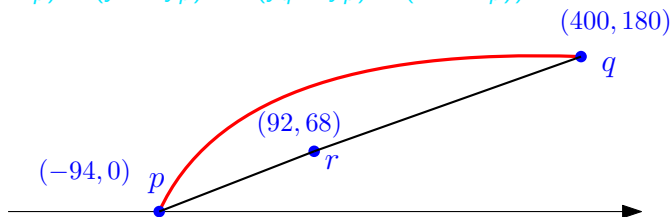


$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

$$\begin{array}{rclclcl} 494 & \times & 68 & - & 186 & \times & 180 & \approx \\ 490 & \times & 68 & - & 190 & \times & 180 & = \\ 33320 & & & - & 34200 & & & \approx \\ 33000 & & & - & 34000 & & & = \end{array}$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$

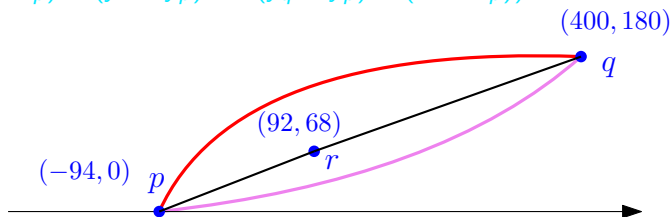


$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

$$\begin{array}{rclcl}
 494 & \times & 68 & - & 186 & \times & 180 & \approx \\
 490 & \times & 68 & - & 190 & \times & 180 & = \\
 33320 & & & - & 34200 & & & \approx \\
 33000 & & & - & 34000 & & & = \\
 & & & & & & & = -1000 !!
 \end{array}$$

Orientation predicate in the toy model

$$\text{sign}((x_q - x_p) \times (y_r - y_p) - (y_q - y_p) \times (x_r - x_p))$$



$$(400 + 94) \times 68 - (92 + 94) \times 180 = 112 \text{ exact}$$

494	×	68	-	186	×	180	≈
490	×	68	-	190	×	180	=
33320			-	34200			≈
33000			-	34000			=
							= -1000 !!

Orientation predicate with double

$$p = (0.5 + x.u, 0.5 + y.u)$$
$$0 \leq x, y < 256, \quad u = 2^{-53}$$
$$q = (12, 12)$$
$$r = (24, 24)$$

Orientation predicate with double

$$p = (0.5 + x.u, 0.5 + y.u)$$
$$0 \leq x, y < 256, \quad u = 2^{-53}$$
$$q = (12, 12)$$
$$r = (24, 24)$$

orientation(p, q, r)
evaluated with double

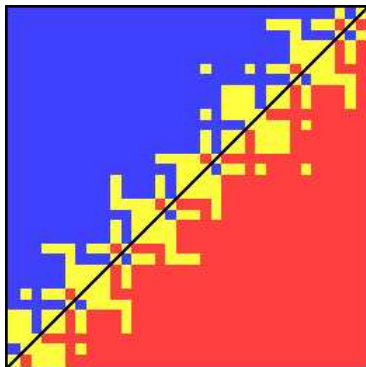
Orientation predicate with double

$$p = (0.5 + x.u, 0.5 + y.u)$$
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$$r = (24, 24)$$

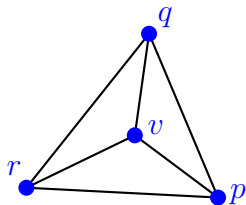
$\text{orientation}(p, q, r)$
evaluated with double

256 x 256 pixel image

> 0, = 0, < 0



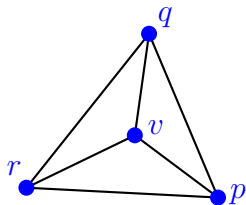
Failure of geometric theorems



pqv, qrv, rpv ccw

$\implies pqr$ ccw

Failure of geometric theorems



pqv, qrv, rpv ccw

$\implies pqv$ ccw

Toy model

p
 $(-94, 0)$

v r
 $(-5, 34)$ $(92, 68)$

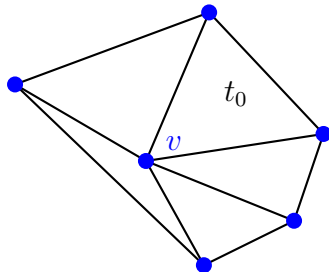
q
 $(400, 180)$

pqv, qrv, rpv ccw

$\longrightarrow pqv$ cw

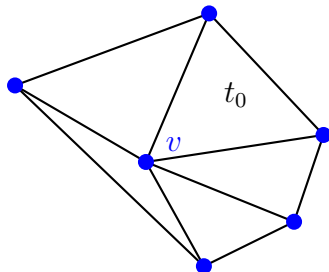
Failure of geometric algorithms

Turn around a vertex



Failure of geometric algorithms

Turn around a vertex



do

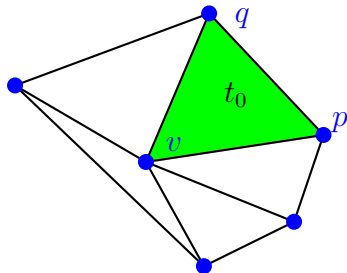
// vpq ccw triangle

go to neighbor through qv

while triangle $\neq t_0$

Failure of geometric algorithms

Turn around a vertex



do

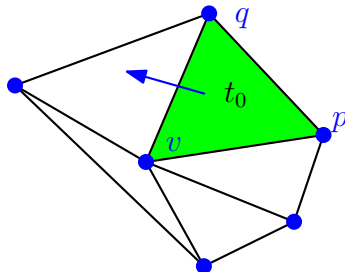
```
// vpq ccw triangle
```

```
go to neighbor through  $qv$ 
```

```
while triangle  $\neq t_0$ 
```

Failure of geometric algorithms

Turn around a vertex



do

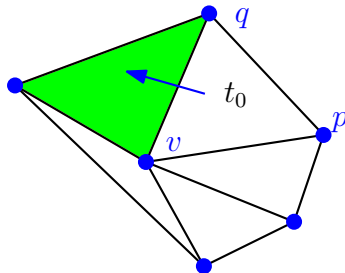
```
// vpq ccw triangle
```

```
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```

```
while triangle  $\neq t_0$ 
```


Failure of geometric algorithms

Turn around a vertex



do

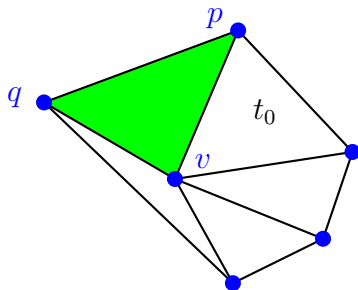
```
// vpq ccw triangle
```

```
go to neighbor through qv
```

```
while triangle  $\neq t_0$ 
```

Failure of geometric algorithms

Turn around a vertex



do

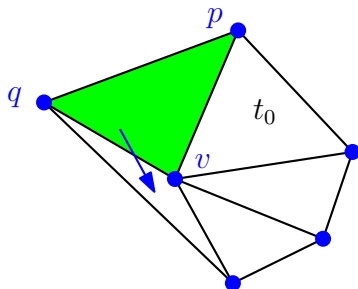
```
// vpq ccw triangle
```

```
go to neighbor through  $qv$ 
```

```
while triangle  $\neq t_0$ 
```

Failure of geometric algorithms

Turn around a vertex



do

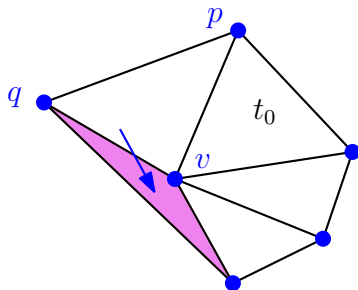
```
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```
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```

```
while triangle  $\neq t_0$ 
```

Failure of geometric algorithms

Turn around a vertex



do

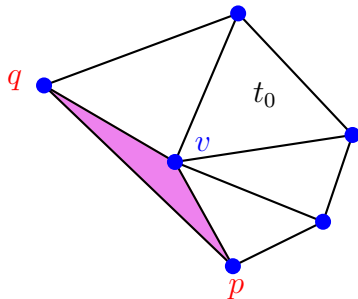
```
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```
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```

```
while triangle  $\neq t_0$ 
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Failure of geometric algorithms

Turn around a vertex



do

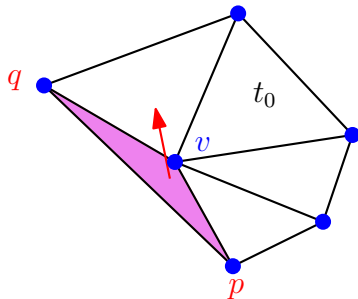
```
// vpq ccw triangle
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```
go to neighbor through  $qv$ 
```

```
while triangle  $\neq t_0$ 
```

Failure of geometric algorithms

Turn around a vertex



do

// vpq ccw triangle

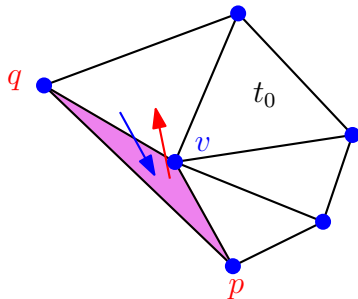
go to neighbor through qv

while triangle $\neq t_0$

LOOP

Failure of geometric algorithms

Turn around a vertex



do

```
// vpq ccw triangle
```

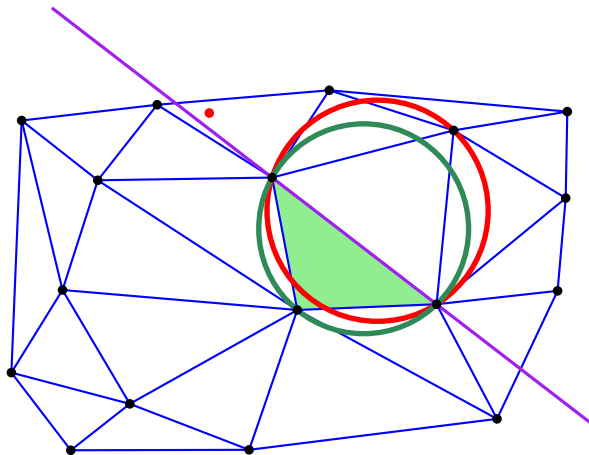
```
go to neighbor through qv
```

```
while triangle  $\neq$   $t_0$ 
```

LOOP

Failure of geometric algorithms

Visibility walk

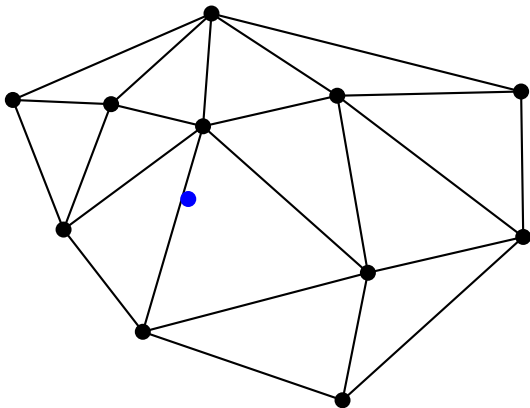


may have **cycles** even in a Delaunay triangulation

see course Delaunay triangulation

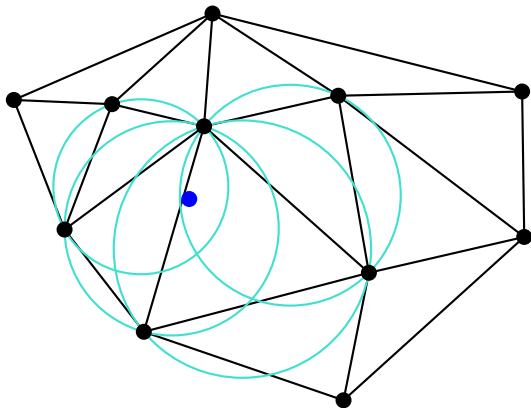
Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation



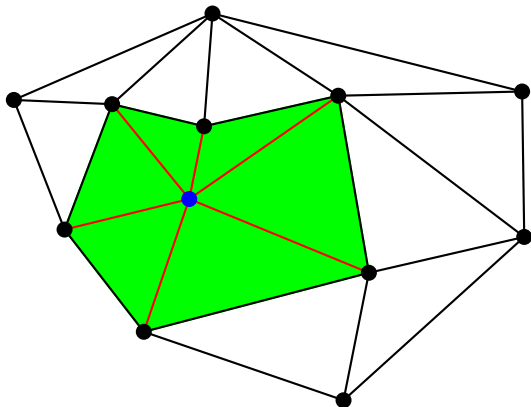
Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation



Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

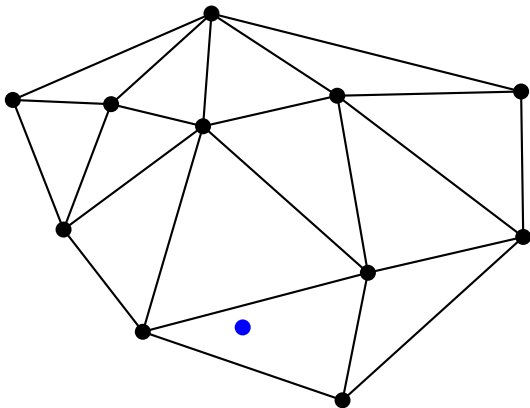


the conflict region is star-shaped

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

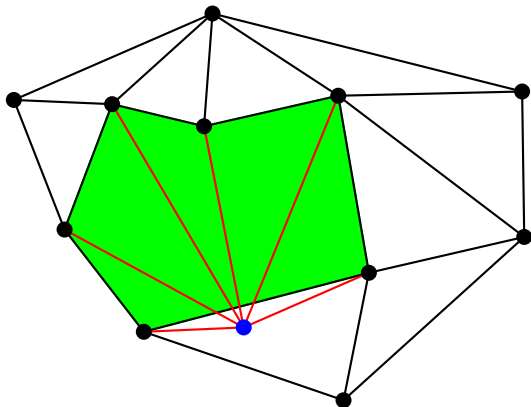
with inexact predicates



Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

with inexact predicates

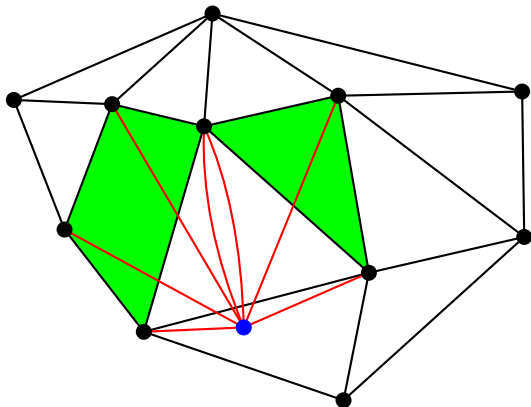


the conflict region is not always star-shaped

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

with inexact predicates

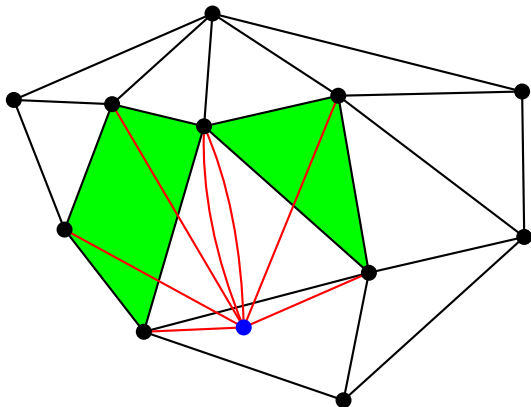


the conflict region is not always star-shaped

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

with inexact predicates

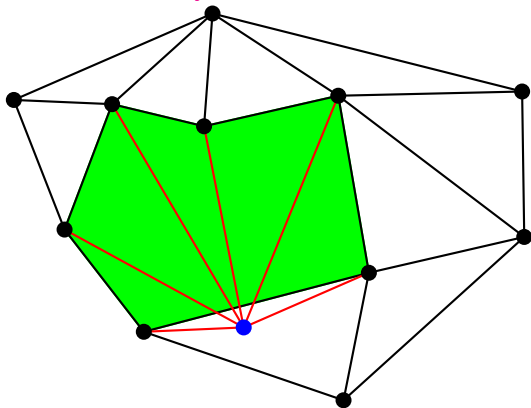


not always combinatorially correct

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

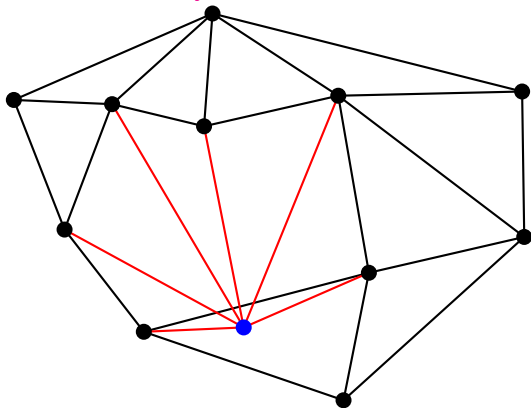
Check combinatorial consistency



Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

Check combinatorial consistency

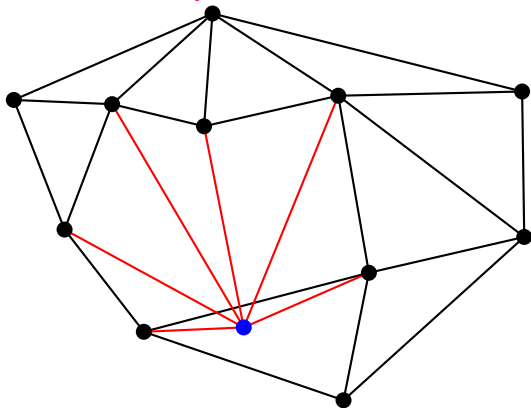


The result is a combinatorial triangulation

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

Check combinatorial consistency

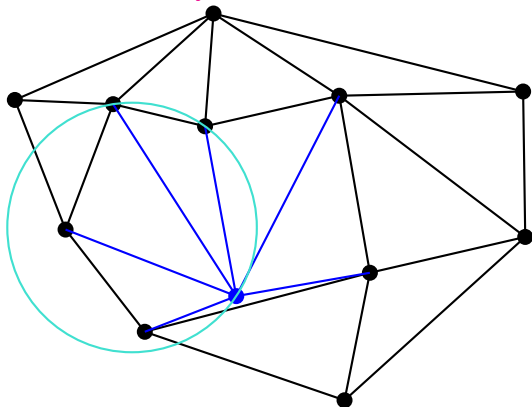


The result is a combinatorial triangulation
but the geometric embedding may have intersecting edges

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

Check combinatorial consistency

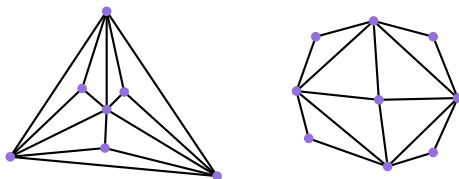


It may not be Delaunay

Solution 1 - Forget about geometric theorems

Insertion in a Delaunay triangulation

Check combinatorial consistency



It may be non combinatorially (strictly) Delaunay

Solution 1 - Forget about geometric theorems

- hardly ever used
- not used any more

Solution 2 - Pretend that we can compute on real numbers

Maybe use a subset of the real numbers

- rational numbers
- algebraic numbers
- ...?

Exact geometric computing

Arithmetic issues — Exact Geometric Computing

1 Introduction

- (Simplified) history
- Robustness: Two main issues

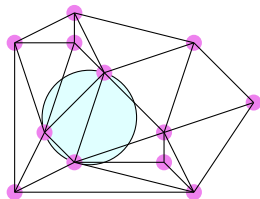
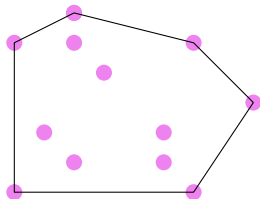
2 Arithmetic issues

- Reminder: floating-point arithmetic
- Consequences
- Exact Geometric Computing

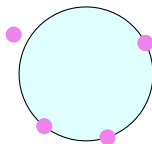
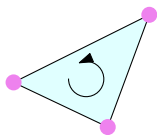
3 Degenerate cases

Predicates

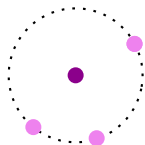
Result of a combinatorial algorithm



depends on **decisions** based on the evaluation of **predicates**:
 set of points $\mapsto \{-1, 0, 1\}$



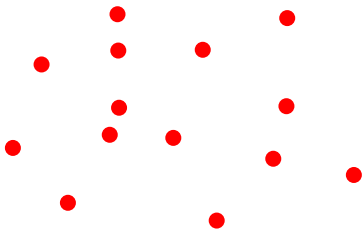
Predicates vs. constructions



construction of a new geometric object

Predicates vs. constructions

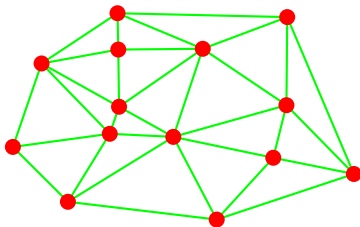
Algorithms



Predicates vs. constructions

Algorithms

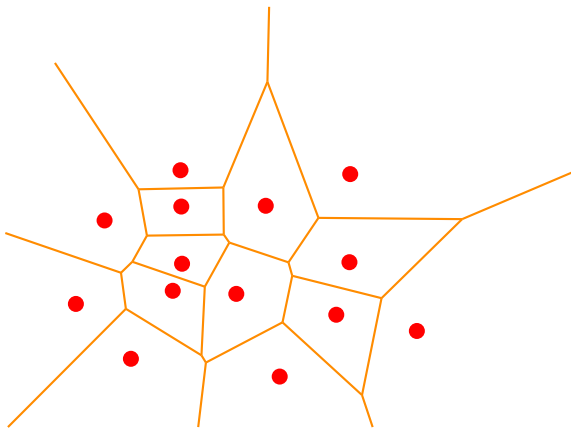
based on **predicates**



Predicates vs. constructions

Algorithms

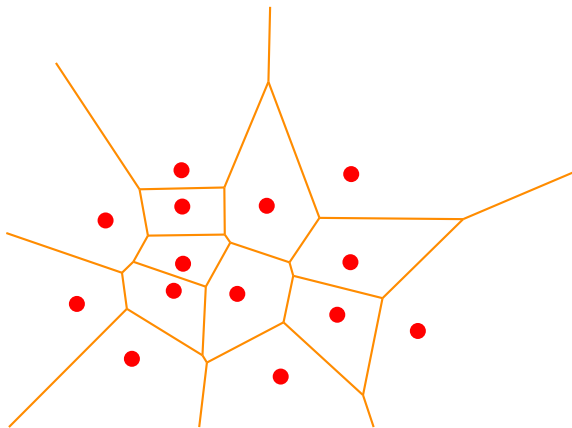
based on **constructions**



Predicates vs. constructions

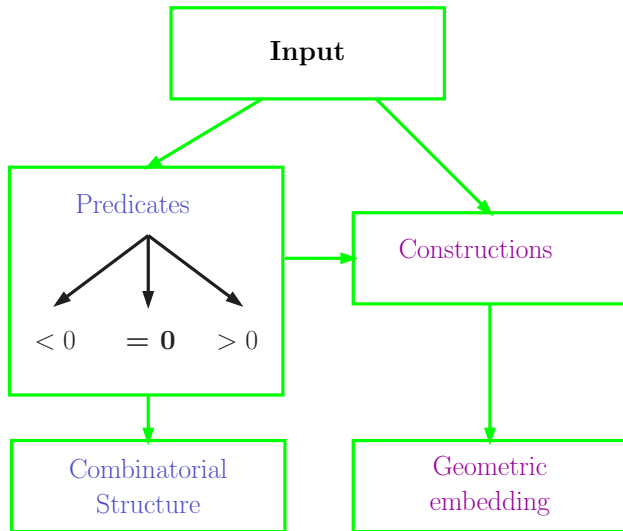
Algorithms

based on **constructions**



→ the underlying combinatorial structure only needs **predicates**

Predicates vs. constructions

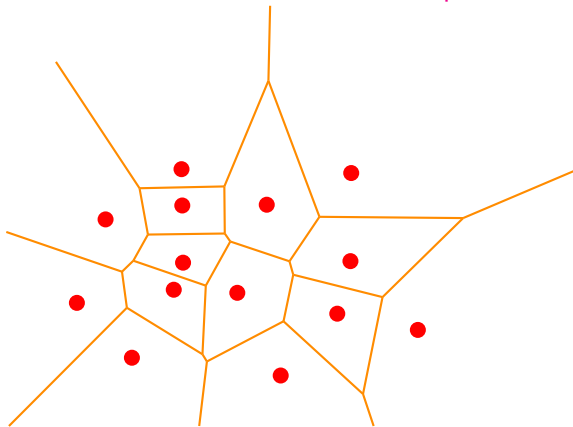


Exact geometric computing

Exact arithmetics ?

Exact geometric computing

Exact arithmetics \rightarrow Exact predicates

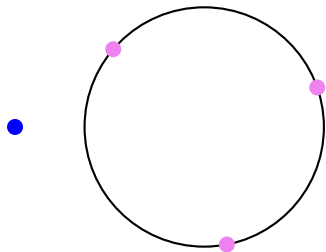


sufficient to get a correct underlying combinatorial structure
constructions can be approximate

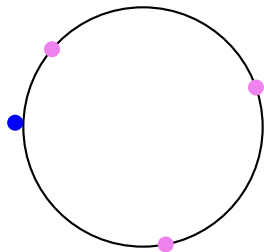
Exact geometric computing

Exact arithmetics \rightarrow Exact predicates

filtered computations



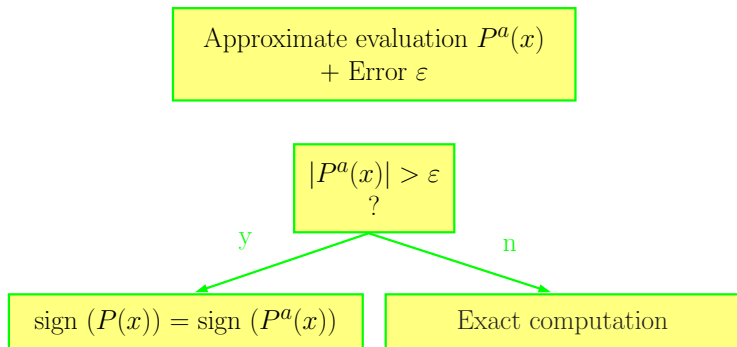
easy cases
exact computation
unnecessary



difficult cases
exact computation
necessary

Filtering

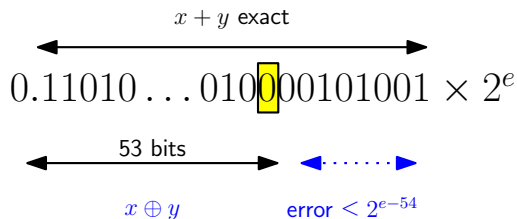
Predicate = sign of a polynomial expression $P(x)$
(x = coordinates)



easy cases are more frequent

\implies cost \simeq cost of approximate (double) computation

Controlling the error



$$x + y = x \oplus y + \varepsilon_{x+y}$$

$$2^{e-1} \leq |x + y| < 2^e \leq 2|x + y| \implies$$

$$\varepsilon_{x+y} \leq 2^{e-54} \leq |x + y| 2^{-53}$$

and similarly for other operations

Static filtering

Known bound on all input coordinates: $|x_i|, |y_i| \leq M$

Static filtering

Known bound on all input coordinates: $|x_i|, |y_i| \leq M$

Example: orientation predicate

$$\begin{vmatrix} x_q - x_p & x_r - x_p \\ y_q - y_p & y_r - y_p \end{vmatrix}$$

Static filtering

Known bound on all input coordinates: $|x_i|, |y_i| \leq M$

Example: orientation predicate

$$\begin{vmatrix} x_q - x_p & x_r - x_p \\ y_q - y_p & y_r - y_p \end{vmatrix}$$

$$x_i - x_p = x_i \ominus x_p + \varepsilon_{x_i - x_p}$$

$$|x_i - x_p| \leq 2M$$

$$\varepsilon_{x_i - x_p} \leq |x_i - x_p| 2^{-53} \leq 2M 2^{-53} \leq 2^{-52} M$$

Static filtering

Known bound on all input coordinates: $|x_i|, |y_i| \leq M$

Example: orientation predicate

$$\begin{vmatrix} x_q - x_p & x_r - x_p \\ y_q - y_p & y_r - y_p \end{vmatrix}$$

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$$|x_i - x_p| \leq 2M$$

$$\varepsilon_{x_i - x_p} \leq |x_i - x_p| 2^{-53} \leq 2M 2^{-53} \leq 2^{-52} M$$

$$\begin{aligned} (x_i - x_p)(y_i - y_p) &= (x_i - x_p) \otimes (y_i - y_p) + \varepsilon_{\otimes} \\ &= (x_i \ominus x_p + \varepsilon_{x_i - x_p}) \otimes (y_i \ominus y_p + \varepsilon_{y_i - y_p}) + \varepsilon_{\otimes} \\ &= \dots \end{aligned}$$

$$|(x_i - x_p)(y_i - y_p)| \leq 4M^2$$

$$\varepsilon_{(x_i - x_p)(y_i - y_p)} \leq 2(2M 2^{-52} M) + 2^{-53} 4M^2$$

$$= 3 \cdot 2^{-51} M^2$$

Static filtering

$$|(x_i - x_p)(y_i - y_p)| \leq 4M^2$$

$$\varepsilon_{(x_i - x_p)(y_i - y_p)} \leq 3 \cdot 2^{-51} M^2$$

$$\text{orient}(p, q, r) = \begin{vmatrix} x_q - x_p & x_r - x_p \\ y_q - y_p & y_r - y_p \end{vmatrix}$$

$$|\text{orient}(p, q, r)| \leq 8M^2$$

$$\varepsilon_{\text{orient}(p, q, r)} \leq 2^{-53} 8M^2 + 2 \cdot 3 \cdot 2^{-51} M^2 \leq 2^{-48} M^2$$

Static filtering

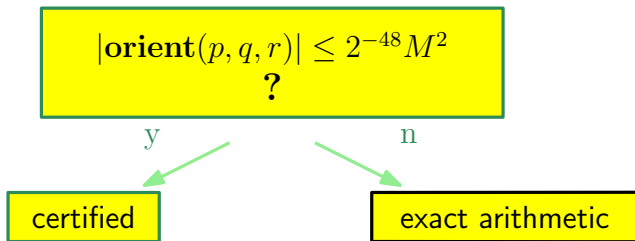
$$|(x_i - x_p)(y_i - y_p)| \leq 4M^2$$

$$\varepsilon_{(x_i - x_p)(y_i - y_p)} \leq 3 \cdot 2^{-51} M^2$$

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Static filtering

-
- hypotheses on input data
 - restricted set of operations
 - error bounds computed manually(?)

Static filtering

-
- hypotheses on input data
 - restricted set of operations
 - error bounds computed manually(?)

- +
- error bounds pre-computed → very fast
 - reasonable success rate

Dynamic filtering

Interval arithmetic

a non representable $\mapsto [\underline{a}, \bar{a}]$

$$[\underline{a}, \bar{a}] + [\underline{b}, \bar{b}] = [\underline{a} \pm \underline{a}, \bar{a} \mp \bar{b}]$$

... error propagation ...

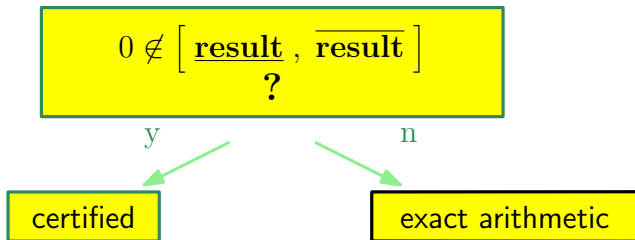
Dynamic filtering

Interval arithmetic

a non representable $\mapsto [\underline{a}, \bar{a}]$

$$[\underline{a}, \bar{a}] + [\underline{b}, \bar{b}] = [\underline{a} \pm \underline{a}, \bar{a} \mp \bar{b}]$$

... error propagation ...



Dynamic filtering

Programming

```
template <class FT>
Orientation orientation
    ( FT px, FT py, FT qx, FT qy, FT rx, FT ry)
{
    return sign( (qx-px)*(ry-py)-(rx-px)*(qy-py) );
}
```

FT = “any” number type, including interval

Dynamic filtering

-
- slower
 - error computed at runtime
 - 2 changes of rounding mode for each predicate call

Dynamic filtering

—

- slower

- error computed at runtime
- 2 changes of rounding mode for each predicate call



- no hypotheses on input data
- excellent success rate
- large set of operations (if intervals can be computed)

Remarks

- Static and dynamic filtering can be combined

Remarks

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- # of arithmetic operations
→ constant in $O(\)$

Remarks

- Static and dynamic filtering can be combined
- # of arithmetic operations
→ constant in $O(\)$
- Degree of predicate
→ size of numbers for exact arithmetic
→ precision of rounding

Conclusion

Exact **predicates**

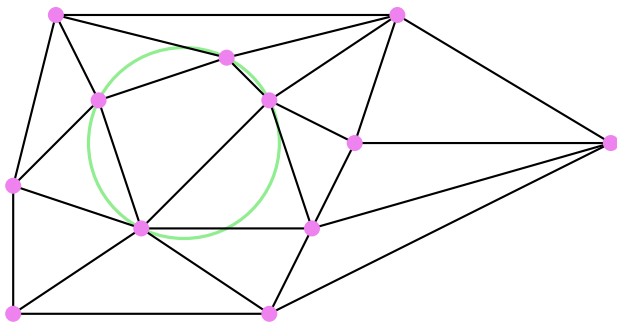
- a way to ensure consistency
- does not mean exact arithmetic

Degenerate cases

- 1 Introduction
 - (Simplified) history
 - Robustness: Two main issues
- 2 Arithmetic issues
 - Reminder: floating-point arithmetic
 - Consequences
 - Exact Geometric Computing
- 3 Degenerate cases

“The” Delaunay “triangulation”?

A polygonization?

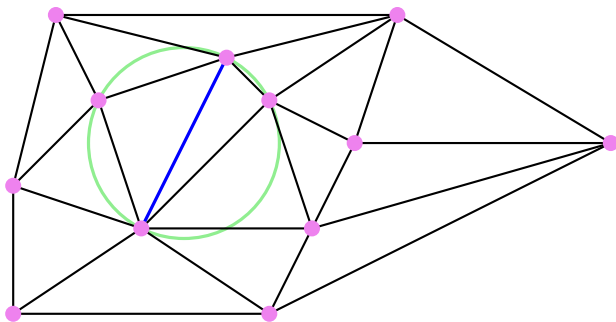


would require to treat all degenerate cases explicitly
and more general data structures \rightsquigarrow non-constant access

“The” Delaunay “triangulation”?

A polygonization?

Triangulation **not uniquely defined**

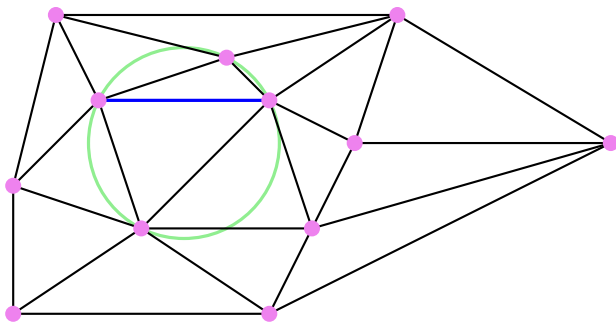


requires consistent choices

“The” Delaunay “triangulation”?

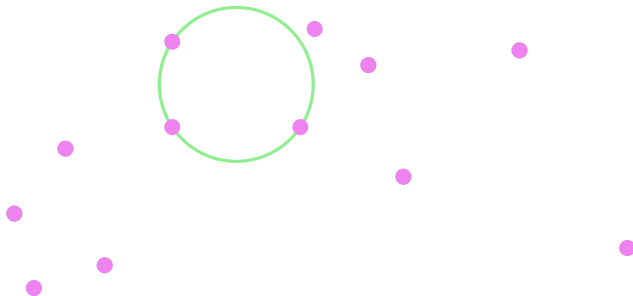
A polygonization?

Triangulation **not uniquely defined**



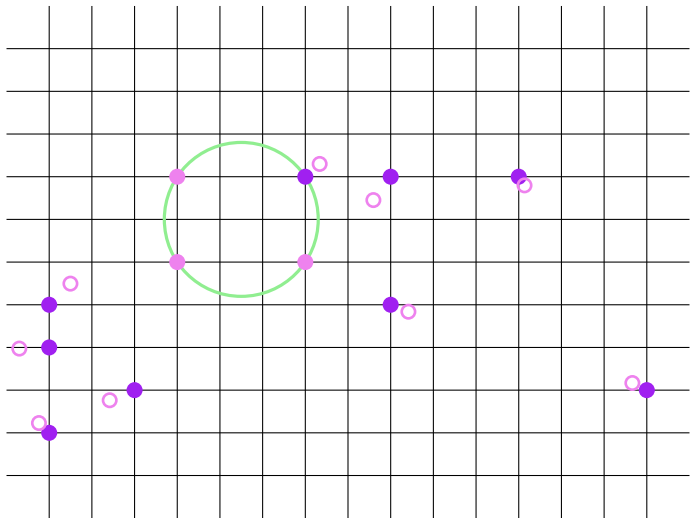
requires consistent choices

It never happens in practice

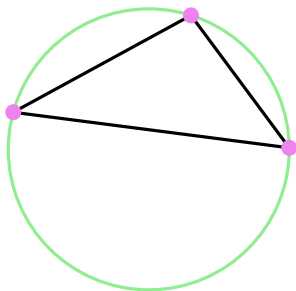


It never happens in practice

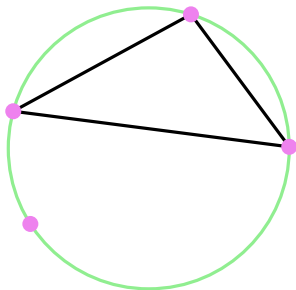
input data are discrete



Simulating the absence of degeneracies

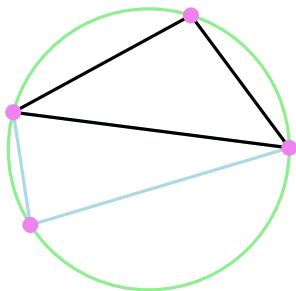


Simulating the absence of degeneracies



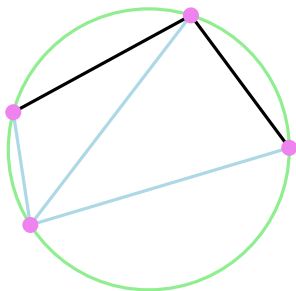
?

Simulating the absence of degeneracies



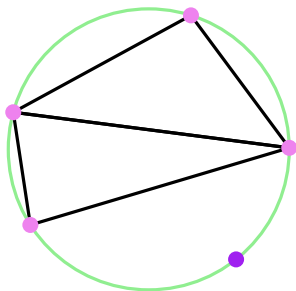
? *as if* new point “outside disk”

Simulating the absence of degeneracies



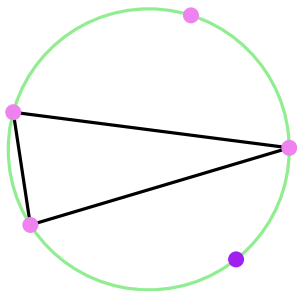
? *as if* new point “in disk”

Random Choices?



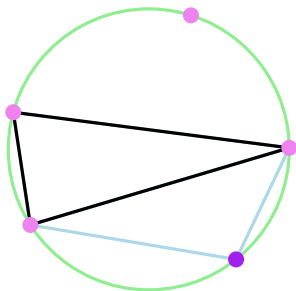
?

Random Choices?



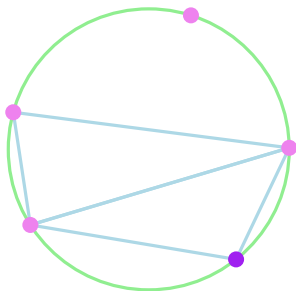
?

Random Choices?



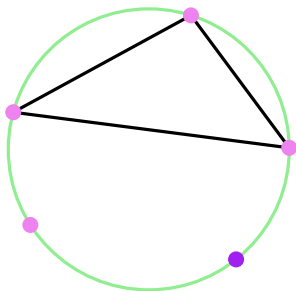
random choice: new point “outside”

Random Choices?



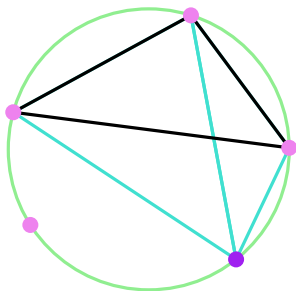
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Random Choices?



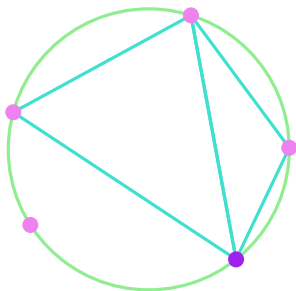
?

Random Choices?



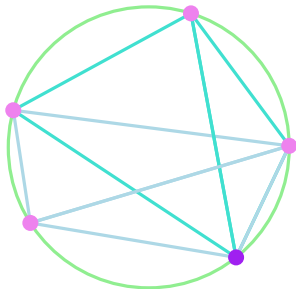
random choice: new point "inside"

Random Choices?



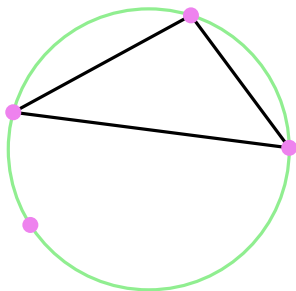
random choice: new point “inside”

Random Choices?



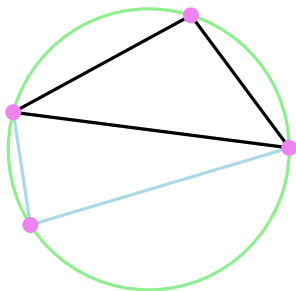
inconsistency

A strategy?



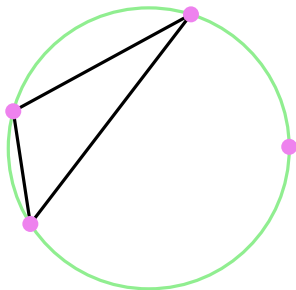
?

A strategy?



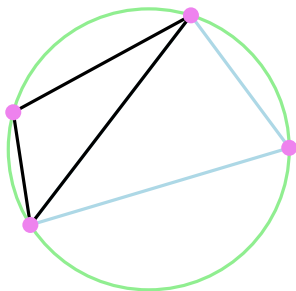
strategy: new point “outside”

A strategy?



strategy: new point “outside”
same points, different order

A strategy?



strategy: new point “outside”

same points, different order

→ different results

(and still sometimes inconsistencies)

Controlled perturbations

A way to ensure consistent choices

Degenerate input

Data perturbed by small epsilons

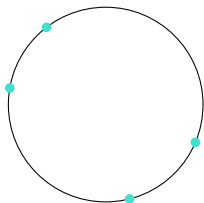
Requires careful control of epsilons
to ensure that perturbed data is non-degenerate

Symbolic perturbations

A way to ensure consistent choices

Input data \mapsto data depending on a **symbolic** parameter ε

- $\varepsilon = 0$: (maybe) degenerate problem

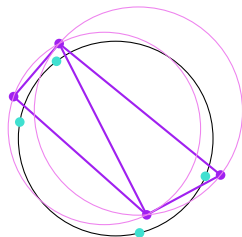


Symbolic perturbations

A way to ensure consistent choices

Input data \mapsto data depending on a **symbolic** parameter ε

- $\varepsilon = 0$: (maybe) degenerate problem
- $\varepsilon \neq 0$: non-degenerate problem \mapsto Result(ε)

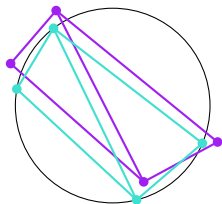


Symbolic perturbations

A way to ensure consistent choices

Input data \mapsto data depending on a **symbolic** parameter ε

- $\varepsilon = 0$: (maybe) degenerate problem
- $\varepsilon \neq 0$: non-degenerate problem \mapsto $\text{Result}(\varepsilon)$



Final result = $\lim_{\varepsilon \rightarrow 0^+} \text{Result}(\varepsilon)$

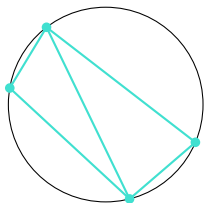
Result is discrete
constant for small ε

Symbolic perturbations

A way to ensure consistent choices

Input data \mapsto data depending on a **symbolic** parameter ε

- $\varepsilon = 0$: (maybe) degenerate problem
- $\varepsilon \neq 0$: non-degenerate problem \mapsto $\text{Result}(\varepsilon)$



Final result = $\lim_{\varepsilon \rightarrow 0^+} \text{Result}(\varepsilon)$

Result is discrete
constant for small ε

SoS = Simulation of Simplicity

Input: n points $p_i = (x_i, y_i), i = 1, \dots, n$

Perturb data: $\forall i, (x_i, y_i) \mapsto (x_i, y_i) + \varepsilon^{2^i} (i, i^2)$

SoS = Simulation of Simplicity

Input: n points $p_i = (x_i, y_i), i = 1, \dots, n$

Perturb data: $\forall i, (x_i, y_i) \mapsto (x_i, y_i) + \varepsilon^{2^i} (i, i^2)$

$$\text{Example: orient}(O, p_i, p_j) = \text{sign} \begin{vmatrix} x_i & x_j \\ y_i & y_j \end{vmatrix}$$

$$i = 3, j = 1, \text{sign} \begin{vmatrix} x_3 & x_1 \\ y_3 & y_1 \end{vmatrix}$$

$$\begin{vmatrix} x_3 + 3\varepsilon^8 & x_1 + \varepsilon^2 \\ y_3 + 9\varepsilon^8 & y_1 + \varepsilon^2 \end{vmatrix} =$$

$$\begin{vmatrix} x_3 & x_1 \\ y_3 & y_1 \end{vmatrix} + \varepsilon^2 \begin{vmatrix} x_3 & 1 \\ y_3 & 1 \end{vmatrix} + \varepsilon^8 \begin{vmatrix} 3 & x_1 \\ 9 & y_1 \end{vmatrix} + \varepsilon^{10} \begin{vmatrix} 3 & 1 \\ 9 & 1 \end{vmatrix}$$

non-null polynomial

sign = sign of first non-null coefficient

SoS = Simulation of Simplicity

+

- general method (?)

SoS = Simulation of Simplicity

+

- general method (?)

-

- requires to check that it works for each necessary predicate
- heavy
- depends on an indexing of the points

Perturbing the world

Example: comparison of abscissae
 $\text{sign}(x_2 - x_1)$

$$(x, y) \mapsto (x + \varepsilon y, y)$$

$$\begin{aligned}x_2 - x_1 &\mapsto (x_2 + \varepsilon y_2) - (x_1 + \varepsilon y_1) = \\ &(x_2 - x_1) + \varepsilon(y_2 - y_1)\end{aligned}$$

non-null polynomial (except for equal points)

Perturbing the world for Delaunay

Orientation predicate

$$(x, y) \mapsto (x + \varepsilon y, y + \varepsilon^2 x + \varepsilon^3(x^2 + y^2))$$

$$\begin{vmatrix} 1 & x_p & y_p \\ 1 & x_q & y_q \\ 1 & x_r & y_r \end{vmatrix}$$

\mapsto

$$(1 - \varepsilon^3) \begin{vmatrix} 1 & x_p & y_p \\ 1 & x_q & y_q \\ 1 & x_r & y_r \end{vmatrix} + \varepsilon^3 \begin{vmatrix} 1 & x_p & x_p^2 + y_p^2 \\ 1 & x_q & x_q^2 + y_q^2 \\ 1 & x_r & x_r^2 + y_r^2 \end{vmatrix} + \varepsilon^4 \begin{vmatrix} 1 & y_p & x_p^2 + y_p^2 \\ 1 & y_q & x_q^2 + y_q^2 \\ 1 & y_r & x_r^2 + y_r^2 \end{vmatrix}$$

Perturbing the world for Delaunay

Orientation predicate

p^*, q^*, r^* : projections of p, q, r on the unit paraboloid

null polynomial \implies the projections of p^*, q^*, r^*

- on the (x, y) -plane
- on the (x, z) -plane
- on the (y, z) -plane

are collinear $\implies p^*, q^*, r^*$ are collinear

\implies 2 points among p^*, q^*, r^* are equal

$$(1 - \varepsilon^3) \begin{vmatrix} 1 & x_p & y_p \\ 1 & x_q & y_q \\ 1 & x_r & y_r \end{vmatrix} + \varepsilon^3 \begin{vmatrix} 1 & x_p & x_p^2 + y_p^2 \\ 1 & x_q & x_q^2 + y_q^2 \\ 1 & x_r & x_r^2 + y_r^2 \end{vmatrix} + \varepsilon^4 \begin{vmatrix} 1 & y_p & x_p^2 + y_p^2 \\ 1 & y_q & x_q^2 + y_q^2 \\ 1 & y_r & x_r^2 + y_r^2 \end{vmatrix}$$

Perturbing the world for Delaunay

in_disk predicate

$$(x, y) \mapsto (x + \varepsilon y, y + \varepsilon^2 x + \varepsilon^3(x^2 + y^2))$$

$$\begin{vmatrix} 1 & x_p & y_p & x_p^2 + y_p^2 \\ 1 & x_q & y_q & x_q^2 + y_q^2 \\ 1 & x_r & y_r & x_r^2 + y_r^2 \\ 1 & x_s & y_s & x_s^2 + y_s^2 \end{vmatrix}$$

\mapsto

$$\begin{aligned} & \begin{vmatrix} 1 & x_p & y_p & x_p^2 + y_p^2 \\ 1 & x_q & y_q & x_q^2 + y_q^2 \\ 1 & x_r & y_r & x_r^2 + y_r^2 \\ 1 & x_s & y_s & x_s^2 + y_s^2 \end{vmatrix} + 2\varepsilon \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} \\ & + \varepsilon^2 \begin{vmatrix} 1 & x_p & y_p & y_p^2 \\ 1 & x_q & y_q & y_q^2 \\ 1 & x_r & y_r & y_r^2 \\ 1 & x_s & y_s & y_s^2 \end{vmatrix} + 2\varepsilon^2 \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} + \varepsilon^3 D_{pqrs}(\varepsilon) \end{aligned}$$

Perturbing the world for Delaunay

in_disk predicate

$$(x, y) \mapsto (x + \varepsilon y, y + \varepsilon^2 x + \varepsilon^3(x^2 + y^2))$$

Assume **null polynomial**

$$\begin{aligned}
 & \begin{vmatrix} 1 & x_p & y_p & x_p^2 + y_p^2 \\ 1 & x_q & y_q & x_q^2 + y_q^2 \\ 1 & x_r & y_r & x_r^2 + y_r^2 \\ 1 & x_s & y_s & x_s^2 + y_s^2 \end{vmatrix} + 2\varepsilon \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} \\
 + \varepsilon^2 & \begin{vmatrix} 1 & x_p & y_p & y_p^2 \\ 1 & x_q & y_q & y_q^2 \\ 1 & x_r & y_r & y_r^2 \\ 1 & x_s & y_s & y_s^2 \end{vmatrix} + 2\varepsilon^2 \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} + \varepsilon^3 D_{pqrs}(\varepsilon)
 \end{aligned}$$

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

$$\mathcal{C}(x, y) = ax^2 + by^2 + cxy + dx + ey + f = 0$$

$$\begin{vmatrix} 1 & x_p & y_p & \mathcal{C}(p) \\ 1 & x_q & y_q & \mathcal{C}(q) \\ 1 & x_r & y_r & \mathcal{C}(r) \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix}$$

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

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$$= a \begin{vmatrix} 1 & x_p & y_p & x_p^2 \\ 1 & x_q & y_q & x_q^2 \\ 1 & x_r & y_r & x_r^2 \\ 1 & x_s & y_s & x_s^2 \end{vmatrix} + b \begin{vmatrix} 1 & x_p & y_p & y_p^2 \\ 1 & x_q & y_q & y_q^2 \\ 1 & x_r & y_r & y_r^2 \\ 1 & x_s & y_s & y_s^2 \end{vmatrix} + c \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} \\ + d \cdot 0 + e \cdot 0 + f \cdot 0$$

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

$$\mathcal{C}(x, y) = ax^2 + by^2 + cxy + dx + ey + f = 0$$

$$\begin{vmatrix} 1 & x_p & y_p & \mathcal{C}(p) \\ 1 & x_q & y_q & \mathcal{C}(q) \\ 1 & x_r & y_r & \mathcal{C}(r) \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = 0$$

$$= a \begin{vmatrix} 1 & x_p & y_p & x_p^2 \\ 1 & x_q & y_q & x_q^2 \\ 1 & x_r & y_r & x_r^2 \\ 1 & x_s & y_s & x_s^2 \end{vmatrix} + b \begin{vmatrix} 1 & x_p & y_p & y_p^2 \\ 1 & x_q & y_q & y_q^2 \\ 1 & x_r & y_r & y_r^2 \\ 1 & x_s & y_s & y_s^2 \end{vmatrix} + c \begin{vmatrix} 1 & x_p & y_p & x_p y_p \\ 1 & x_q & y_q & x_q y_q \\ 1 & x_r & y_r & x_r y_r \\ 1 & x_s & y_s & x_s y_s \end{vmatrix} \\ + d \cdot 0 + e \cdot 0 + f \cdot 0$$

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

$$\mathcal{C}(x, y) = ax^2 + by^2 + cxy + dx + ey + f = 0$$

$$\begin{vmatrix} 1 & x_p & y_p & \mathcal{C}(p) \\ 1 & x_q & y_q & \mathcal{C}(q) \\ 1 & x_r & y_r & \mathcal{C}(r) \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = 0$$

$$= \begin{vmatrix} 1 & x_p & y_p & 0 \\ 1 & x_q & y_q & 0 \\ 1 & x_r & y_r & 0 \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = \mathcal{C}(s) \begin{vmatrix} 1 & x_p & y_p \\ 1 & x_q & y_q \\ 1 & x_r & y_r \end{vmatrix} \implies$$

- $s \in \mathcal{C} \forall \mathcal{C}$
- or p, q, r collinear

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

$$\mathcal{C}(x, y) = ax^2 + by^2 + cxy + dx + ey + f = 0$$

$$\begin{vmatrix} 1 & x_p & y_p & \mathcal{C}(p) \\ 1 & x_q & y_q & \mathcal{C}(q) \\ 1 & x_r & y_r & \mathcal{C}(r) \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = 0$$

$$= \begin{vmatrix} 1 & x_p & y_p & 0 \\ 1 & x_q & y_q & 0 \\ 1 & x_r & y_r & 0 \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = \mathcal{C}(s) \begin{vmatrix} 1 & x_p & y_p \\ 1 & x_q & y_q \\ 1 & x_r & y_r \end{vmatrix} \implies$$

- $s \in \mathcal{C} \forall \mathcal{C}$
- or p, q, r collinear

$\implies p, q, r, s$ collinear

Perturbing the world for Delaunay

in_disk predicate

Let \mathcal{C} be a conic through p, q, r

$$\mathcal{C}(x, y) = ax^2 + by^2 + cxy + dx + ey + f = 0$$

$$\begin{vmatrix} 1 & x_p & y_p & \mathcal{C}(p) \\ 1 & x_q & y_q & \mathcal{C}(q) \\ 1 & x_r & y_r & \mathcal{C}(r) \\ 1 & x_s & y_s & \mathcal{C}(s) \end{vmatrix} = 0$$

p, q, r, s cannot be both collinear and cocircular

→ contradiction

the perturbed in_disk polynomial is non-null

Perturbing the world



- general method (?)
- does not need points to be indexed
- lighter computations

Perturbing the world



- general method (?)
- does not need points to be indexed
- lighter computations



- requires to check that it works for each necessary predicate

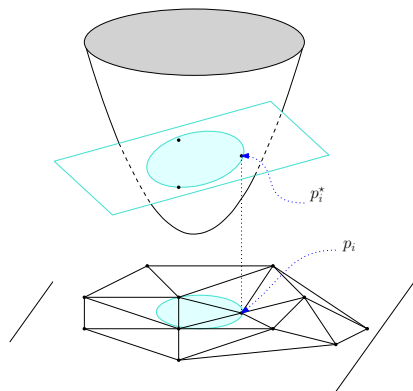
Main drawback for Delaunay

All predicates are perturbed by all the above perturbations

including orientation

↳ these perturbations can lead to flat tetrahedra

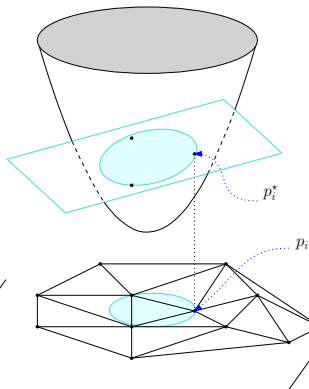
Perturbing points in the $d + 1^{\text{th}}$ dimension



$$p_i = (x_i, y_i)$$

$$p_i^* = (x_i, y_i, t_i = x_i^2 + y_i^2)$$

Perturbing points in the $d + 1^{\text{th}}$ dimension



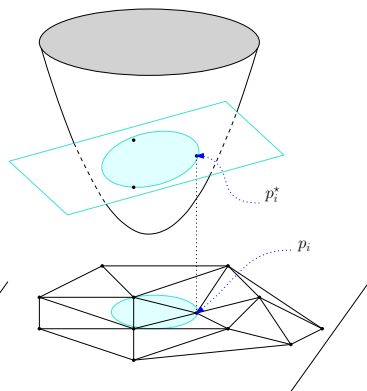
$$p_i = (x_i, y_i)$$

$$p_i^* = (x_i, y_i, t_i = x_i^2 + y_i^2)$$

$$\text{in_disk}(p_i, p_j, p_k, p_l) = \frac{\mathcal{D}(p_i, p_j, p_k, p_l)}{\text{orient}(p_i, p_j, p_k)}$$

$$\mathcal{D}(p_i, p_j, p_k, p_l) = \text{orient}(p_i^*, p_j^*, p_k^*, p_l^*)$$

Perturbing points in the $d + 1^{\text{th}}$ dimension



$$p_i = (x_i, y_i)$$

$$p_i^* = (x_i, y_i, t_i = x_i^2 + y_i^2)$$

$$\mapsto p^{*i\varepsilon} = (x_i, y_i, t_i + \varepsilon^{n-i})$$

$$\text{in_disk}(p_i, p_j, p_k, p_l) = \frac{\mathcal{D}(p_i, p_j, p_k, p_l)}{\text{orient}(p_i, p_j, p_k)}$$

$$\mathcal{D}(p_i, p_j, p_k, p_l) = \text{orient}(p_i^*, p_j^*, p_k^*, p_l^*)$$

$$\mapsto \text{orient}(p^{*i\varepsilon}, p^{*j\varepsilon}, p^{*k\varepsilon}, p^{*l\varepsilon})$$

Perturbing points in the $d + 1^{th}$ dimension

$$\text{orient}(p^{*i\varepsilon}, p^{*j\varepsilon}, p^{*k\varepsilon}, p^{*l\varepsilon}) = \begin{vmatrix} 1 & 1 & 1 & 1 \\ x_i & x_j & x_k & x_l \\ y_i & y_j & y_k & y_l \\ z_i & z_j & z_k & z_l \\ t_i + \varepsilon^{n-i} & t_j + \varepsilon^{n-j} & t_k + \varepsilon^{n-k} & t_l + \varepsilon^{n-l} \end{vmatrix}$$

$$\begin{aligned} &= \mathcal{D}(p_i, p_j, p_k, p_l) \\ &\quad - \text{orient}(p_i, p_j, p_k) \varepsilon^{n-l} \\ &\quad + \text{orient}(p_i, p_j, p_l) \varepsilon^{n-k} \\ &\quad - \text{orient}(p_i, p_k, p_l) \varepsilon^{n-j} \\ &\quad + \text{orient}(p_j, p_k, p_l) \varepsilon^{n-i} \end{aligned}$$

4 cocircular points \longrightarrow **non-null** polynomial in ε

Perturbing points in the $d + 1^{\text{th}}$ dimension

$$\text{orient}(p^{*i\varepsilon}, p^{*j\varepsilon}, p^{*k\varepsilon}, p^{*l\varepsilon}) = \begin{vmatrix} 1 & 1 & 1 & 1 \\ x_i & x_j & x_k & x_l \\ y_i & y_j & y_k & y_l \\ z_i & z_j & z_k & z_l \\ t_i + \varepsilon^{n-i} & t_j + \varepsilon^{n-j} & t_k + \varepsilon^{n-k} & t_l + \varepsilon^{n-l} \end{vmatrix}$$

$$\begin{aligned} &= \mathcal{D}(p_i, p_j, p_k, p_l) \\ &\quad - \text{orient}(p_i, p_j, p_k) \varepsilon^{n-l} \\ &\quad + \text{orient}(p_i, p_j, p_l) \varepsilon^{n-k} \\ &\quad - \text{orient}(p_i, p_k, p_l) \varepsilon^{n-j} \\ &\quad + \text{orient}(p_j, p_k, p_l) \varepsilon^{n-i} \end{aligned}$$

4 cocircular points \longrightarrow **non-null** polynomial in ε

point with highest index
in the disk of the other 3

Perturbing points in the $d + 1^{th}$ dimension

global indexing = lexicographic order

Delaunay triangulation **uniquely defined**

Perturbing points in the $d + 1^{th}$ dimension

global indexing = lexicographic order

Delaunay triangulation **uniquely defined**

+

- **NO flat simplex**
- easy to implement
- does not need points to be globally sorted
- lighter computations

Perturbing points in the $d + 1^{th}$ dimension

global indexing = lexicographic order

Delaunay triangulation **uniquely defined**

+

- **NO flat simplex**
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-

- specific for (weighted) Delaunay triangulations

Perturbing points in the $d + 1^{th}$ dimension

global indexing = lexicographic order

Delaunay triangulation **uniquely defined**

+

- **NO flat simplex**
- easy to implement
- does not need points to be globally sorted
- lighter computations

-

- specific for (weighted) Delaunay triangulations
- result is not (always) the Delaunay triangulation of a non-degenerate set of points
weighted Delaunay triangulation instead