

Convex Hull

A special thanks to

David Wu Robbie Hott and the UVA CS Dept



Outline

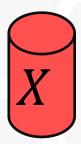
- Reductions and lower bounds
- Convex hull
 - Applications
 - Graham's algorithm (Graham scan)
 - Jarvis' algorithm (Jarvis march)
 - Chan's algorithm

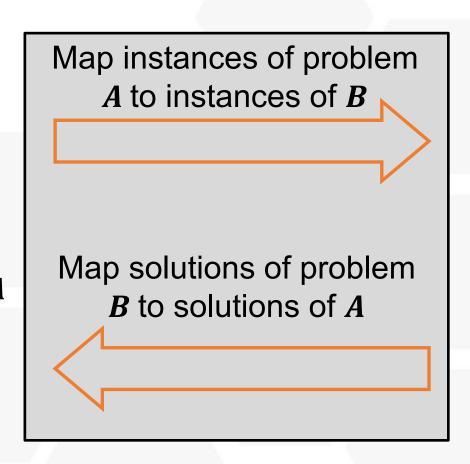
Reductions

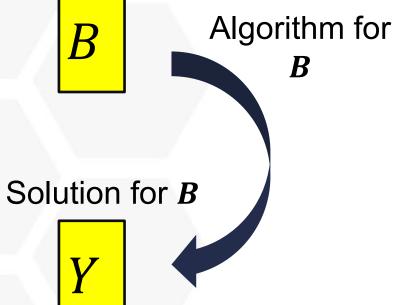
Problem A



Solution for A







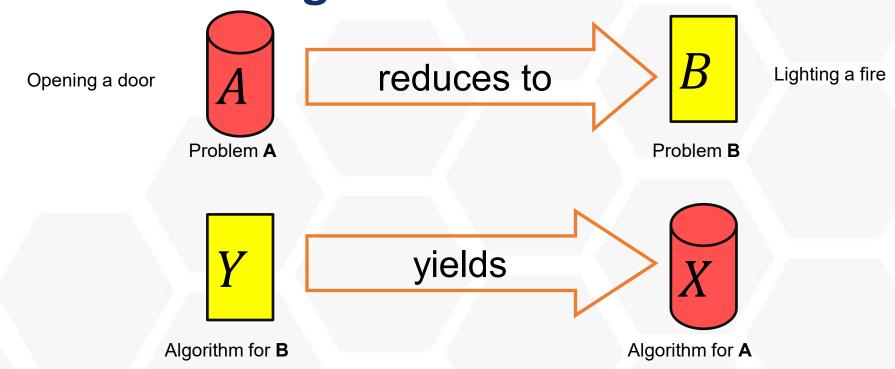
Problem B

Reduction

 $A \leq B$: there is a reduction from A to B

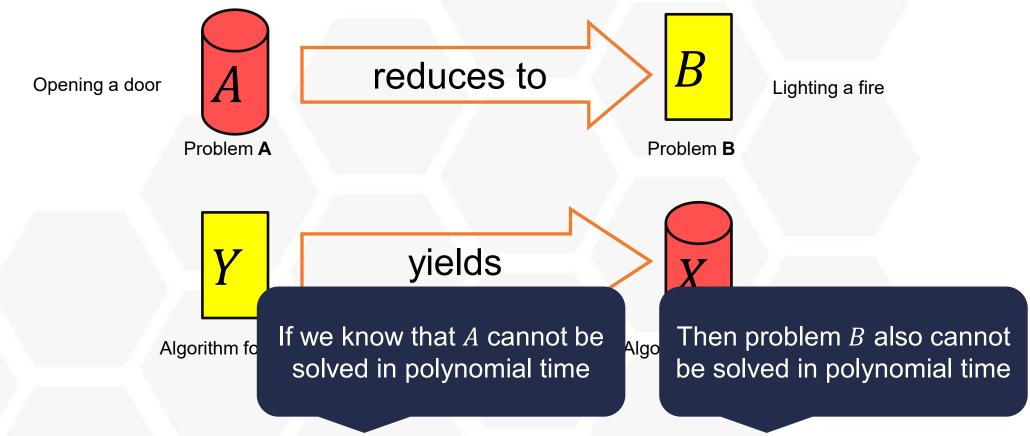


Understanding Reductions



Implication: A is no more difficult than B (denoted $A \leq B$)

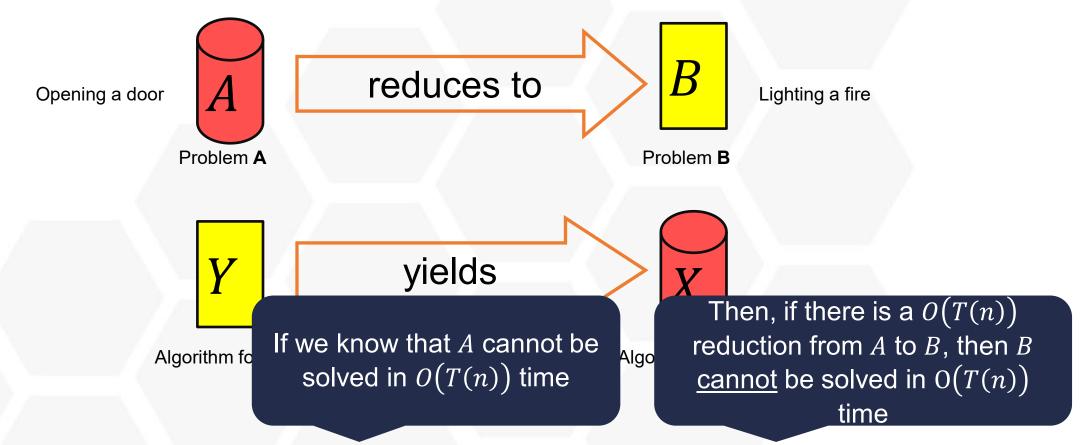
Worst-Case Lower Bounds via Reductions



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Worst-Case Lower Bounds via Reductions



Implication: A is no more difficult than B (denoted $A \leq B$)



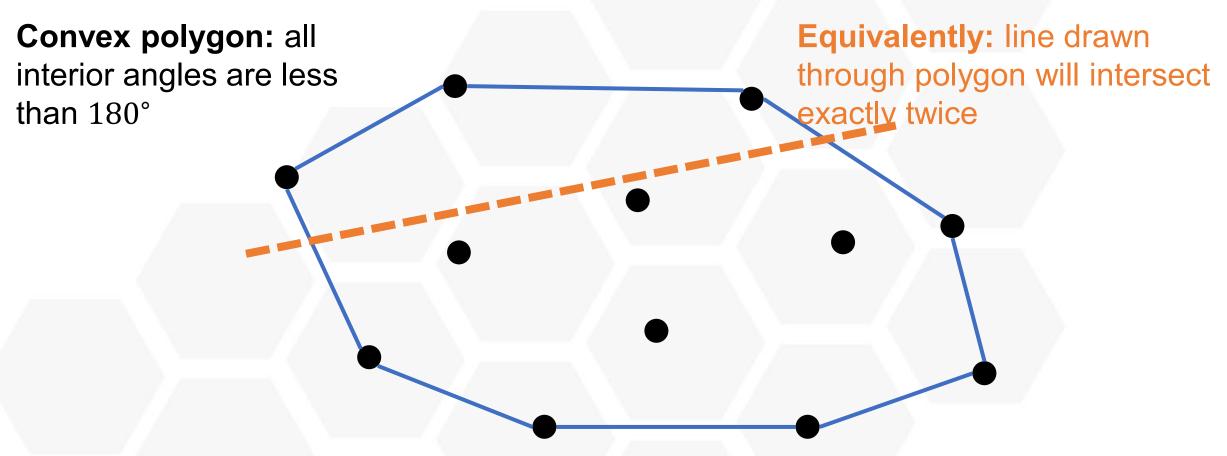
Problem: find the smallest <u>convex</u> polygon that bounds a shape (or more generally, a collection of points)

Example application: collision detection in computer graphics; also useful for solving other problems, especially in <u>computational geometry</u> (e.g., furthest pair of points)

Convex Hull

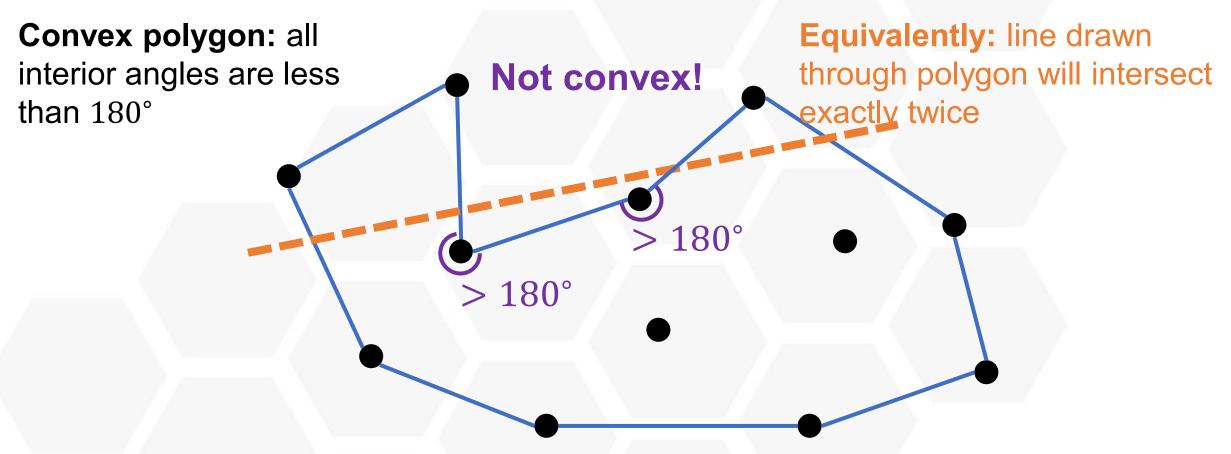
- ▶ Data Science Applications
 - Model to represent data comprised of convex combinations.
 - E.G. Spectral data mixing (and unmixing)
 - Data fusion models: convex combinations
 - Model used in convex optimization





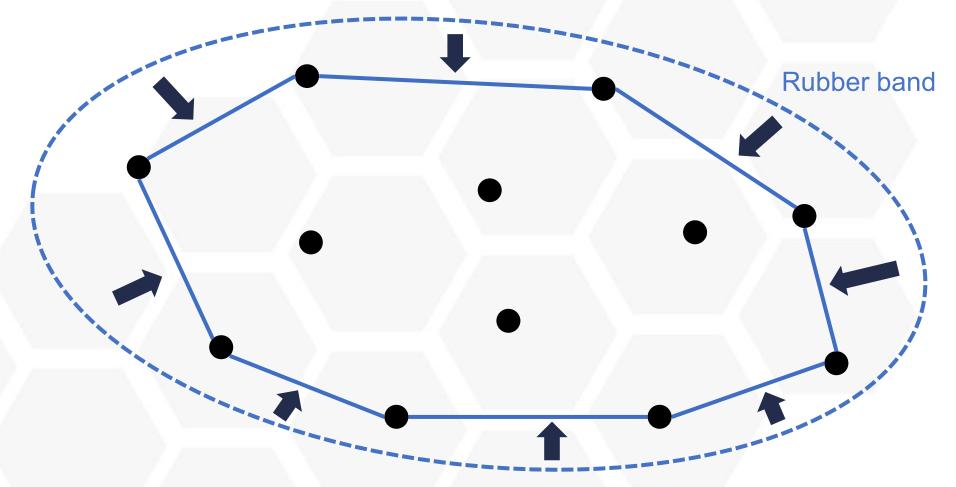
Problem: given a set of n points, find the smallest convex polygon such that every point is either on the boundary or the interior of the polygon



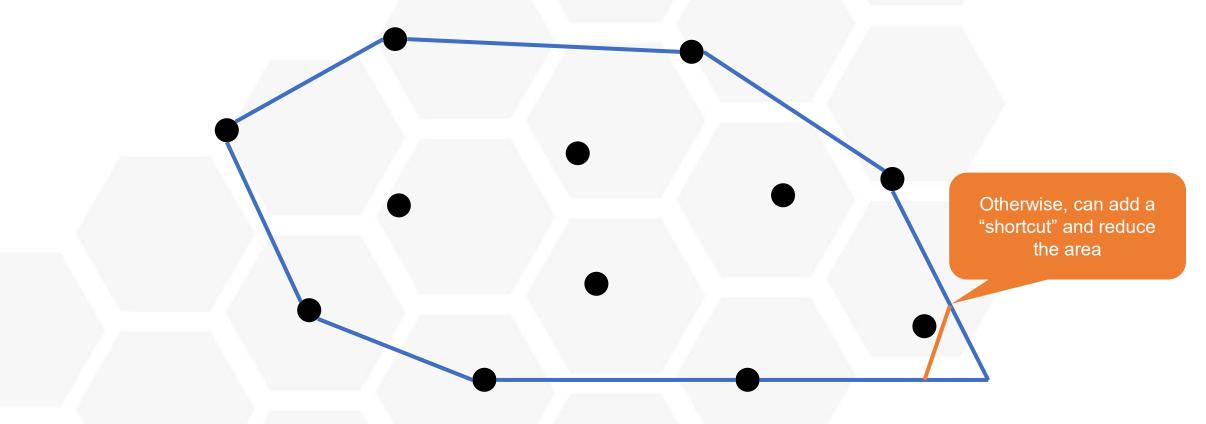


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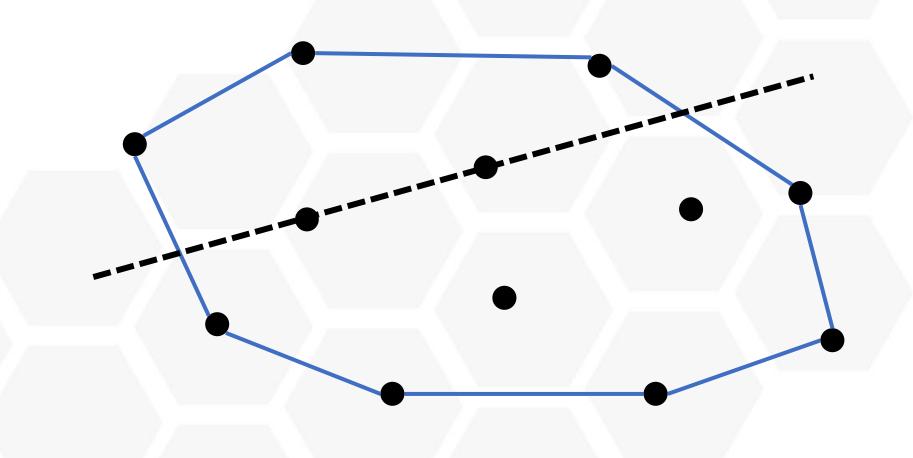


Rubber band analogy: imagine the points are nails sticking out of a board and wrapping a rubber band to encompass the nails; convex hull is resulting shape



Observation: every point on the convex hull is one of the input points

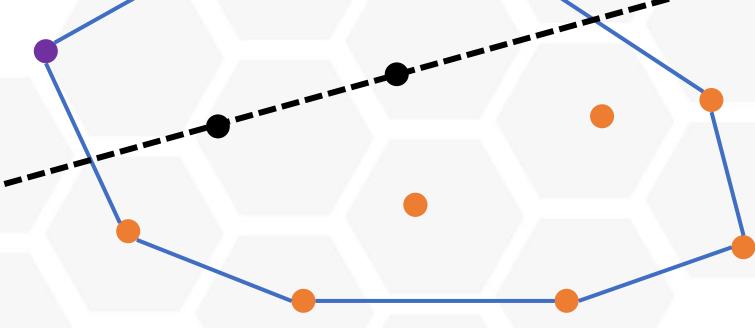
A Brute Force Approach





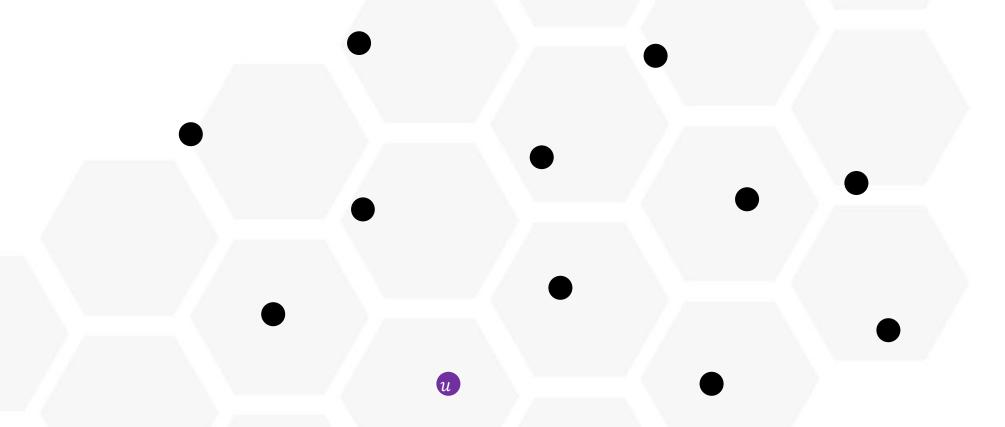
A Brute Force Approach

Observation: if there are points on both sides of the line, then the pair cannot be an edge in the convex hull

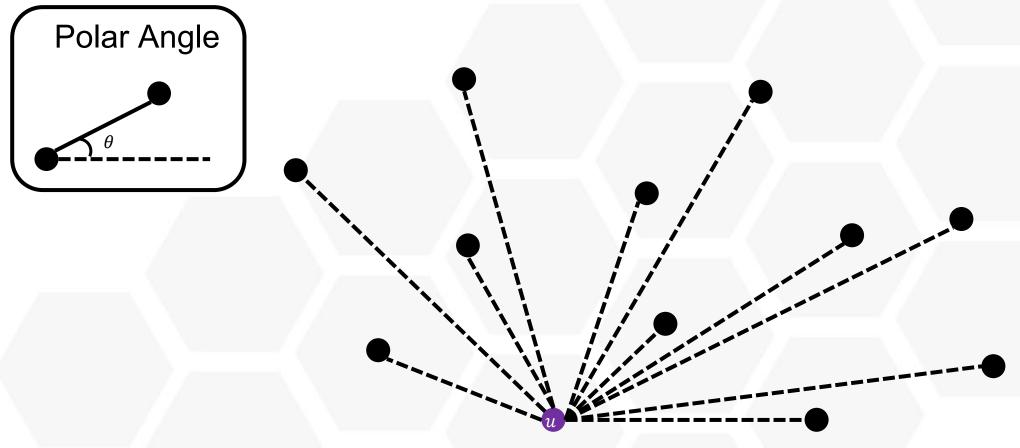


Run-time: $O(n^3)$

Brute force approach: for every pair of points, check if all other points are on the same side of the line

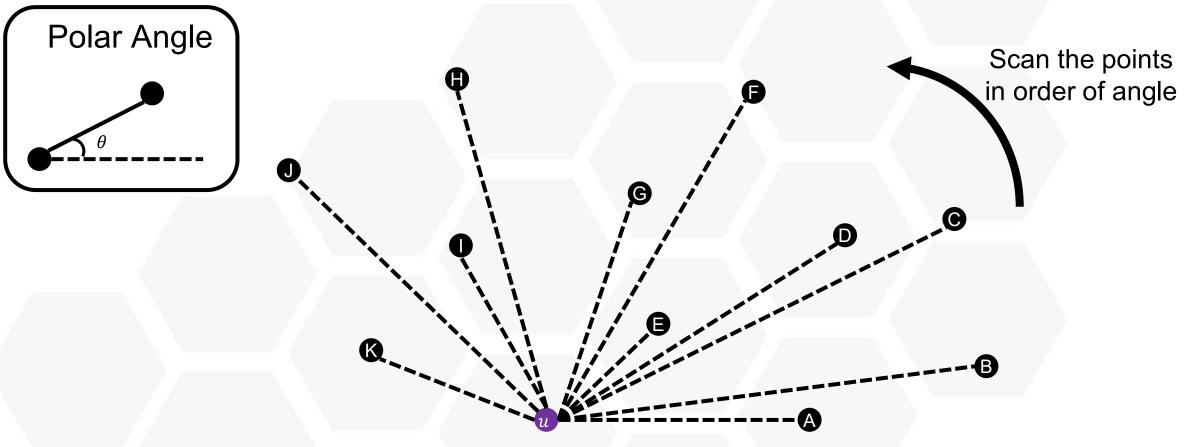


Observation: Extremal points must be part of the convex hull (e.g., bottom-most point, left-most point, etc.)

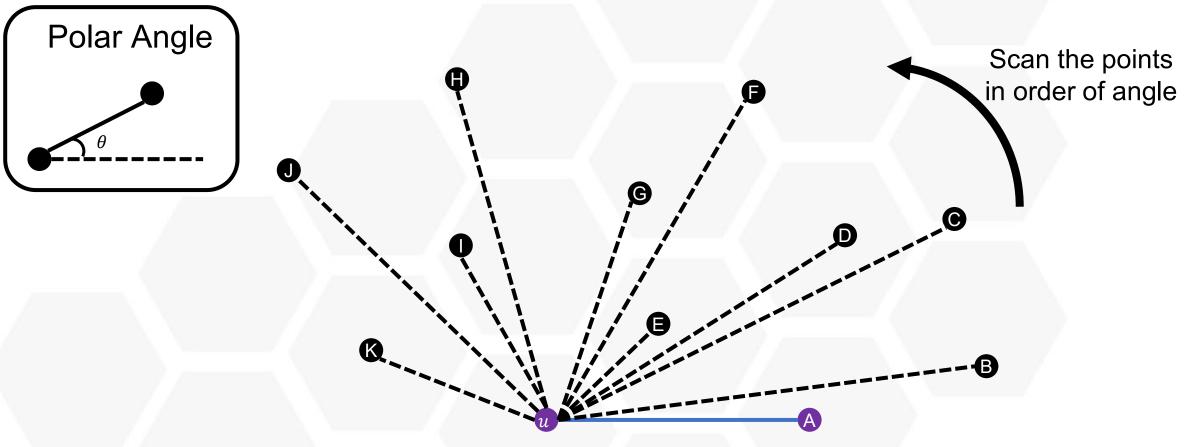


Consider the (polar) angle formed between base point u and every other point

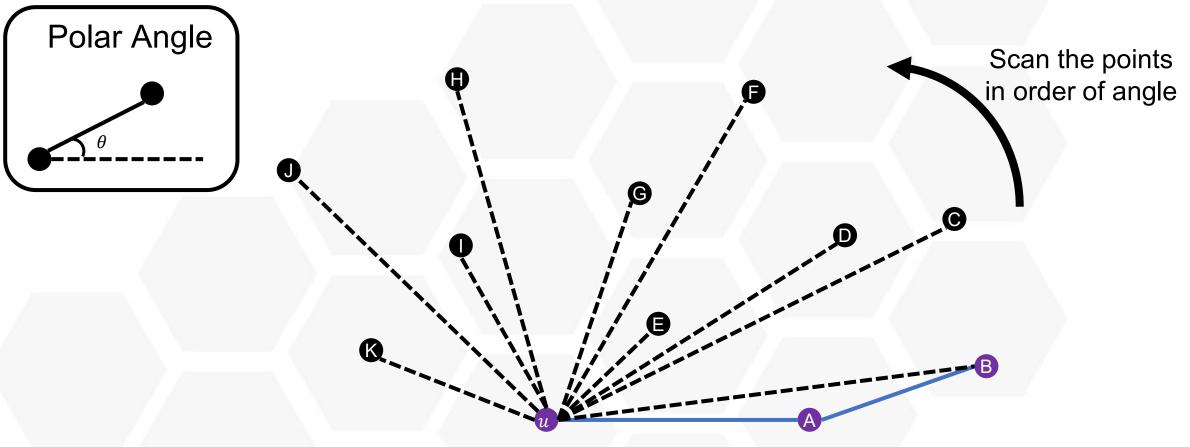




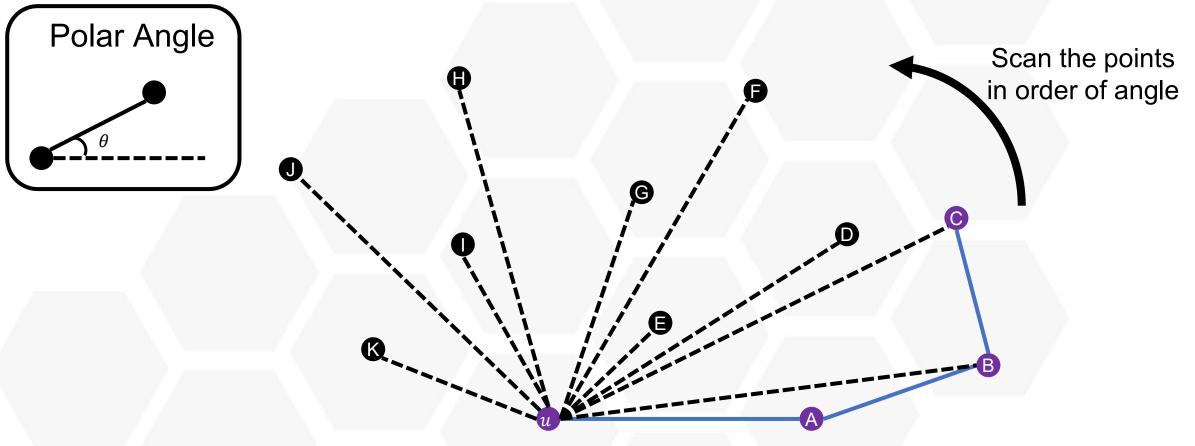




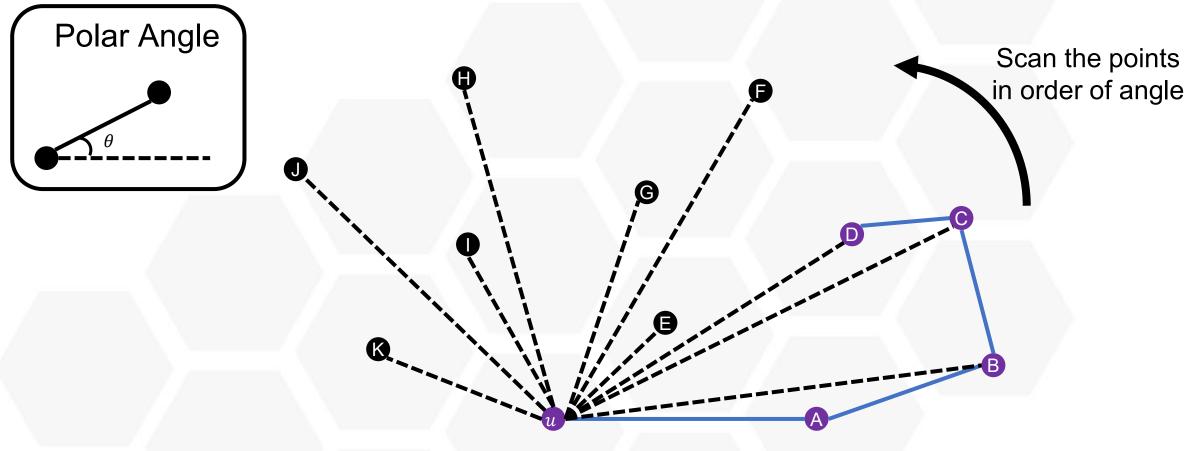




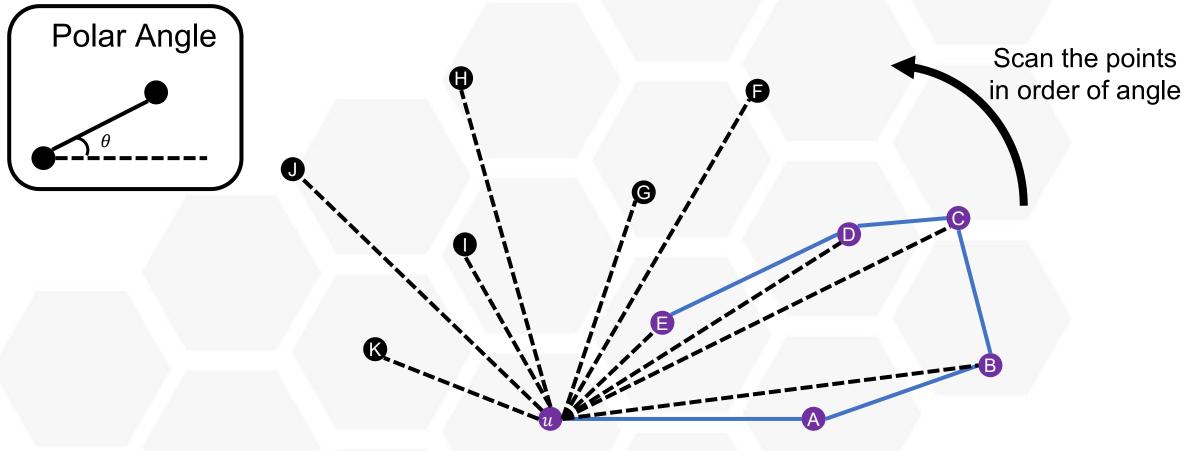




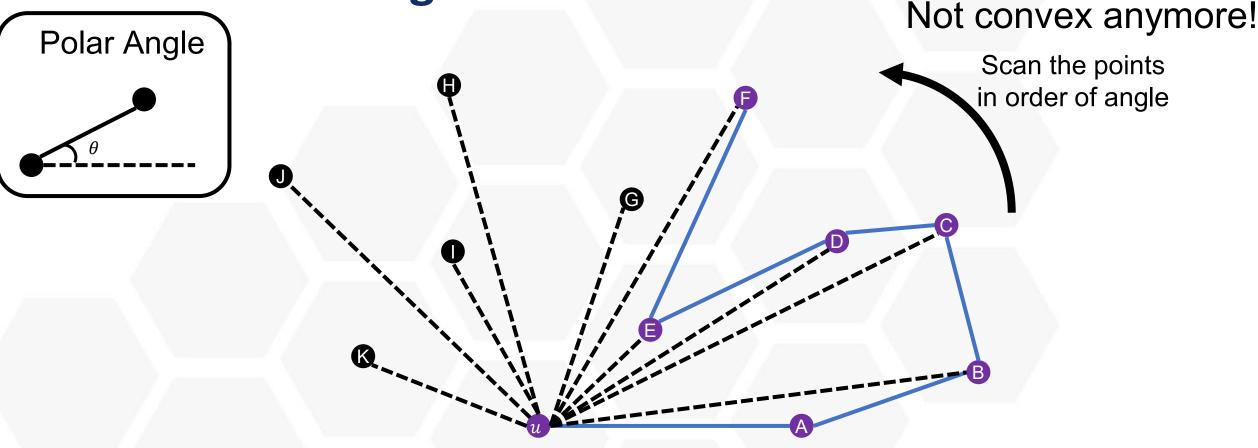




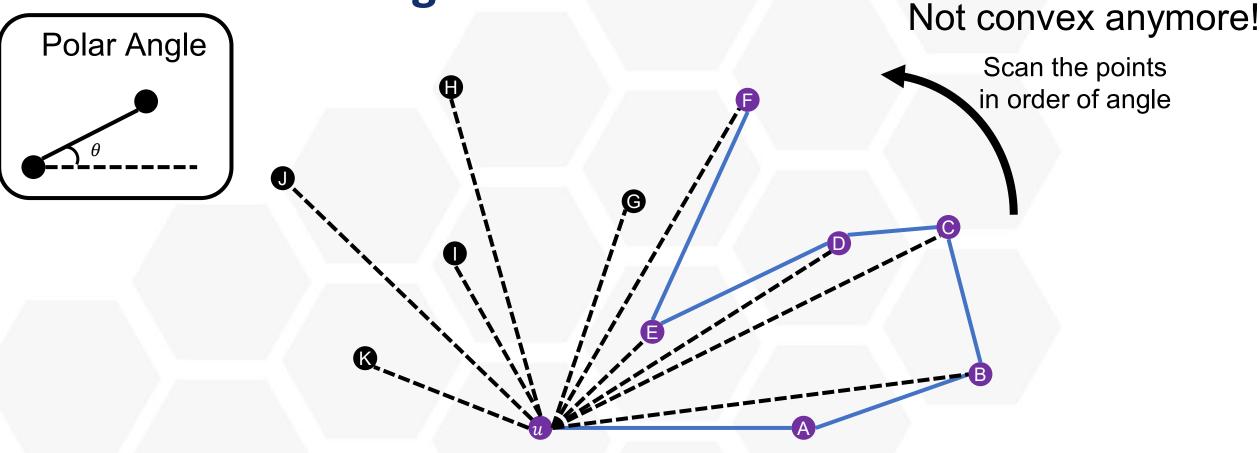






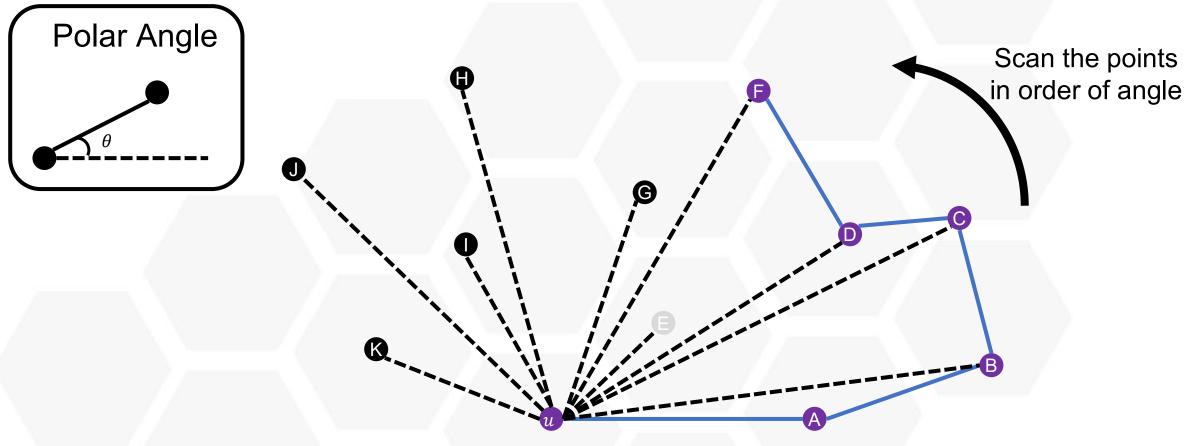






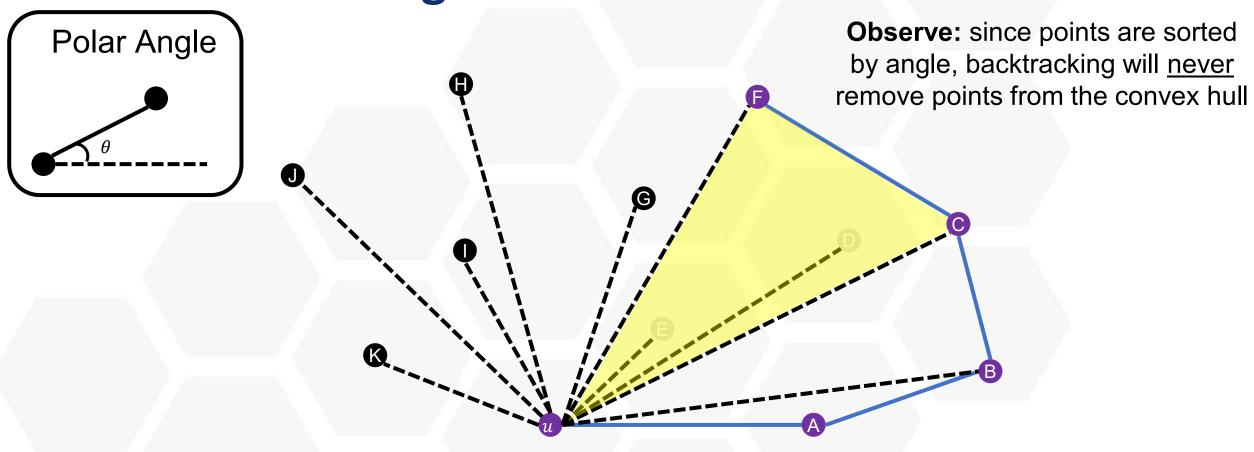
Idea: Try extending the convex hull from the previous vertex if we are unable to extend from the current one





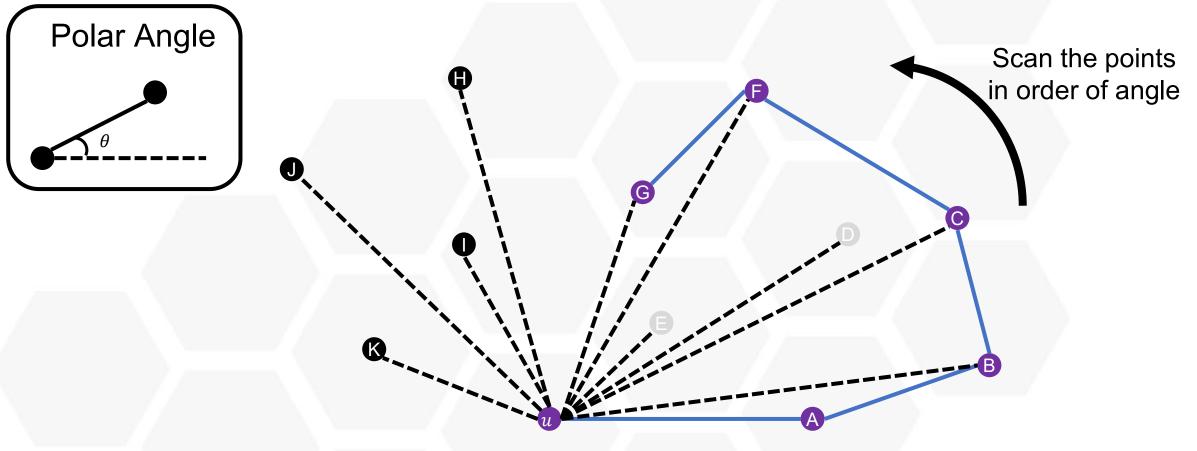
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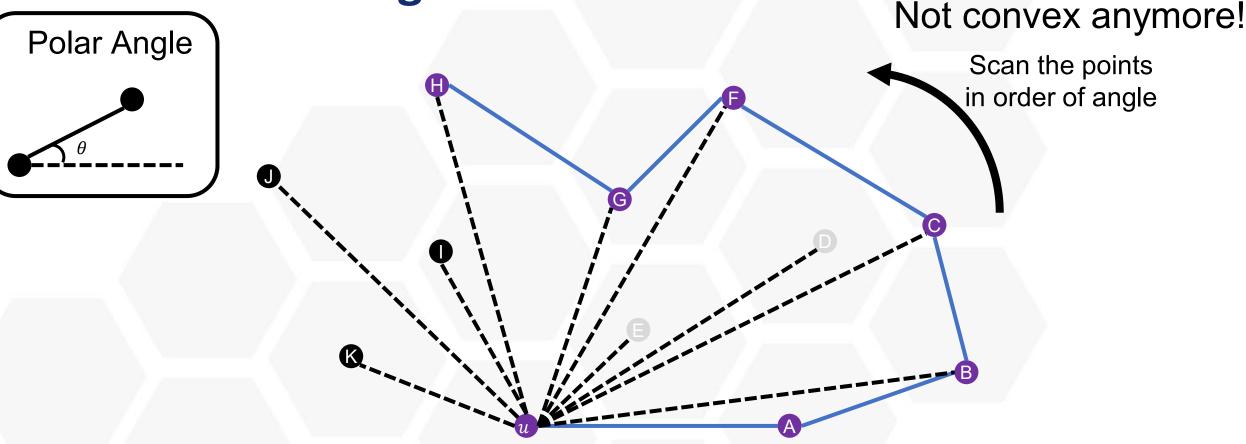


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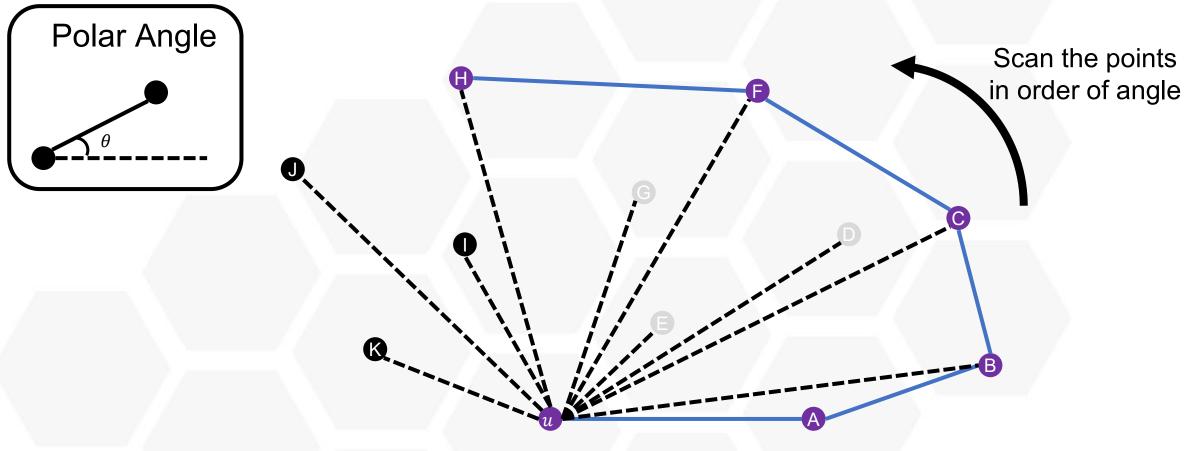




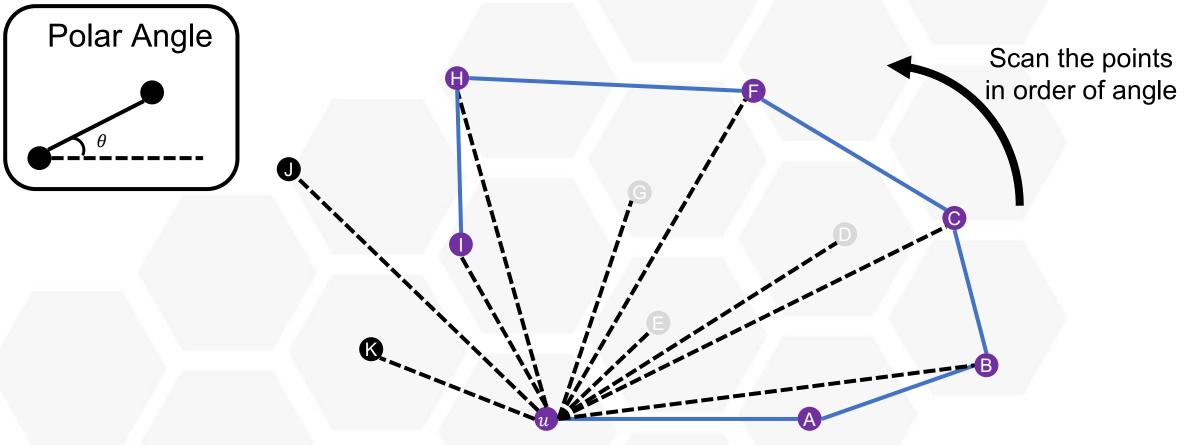








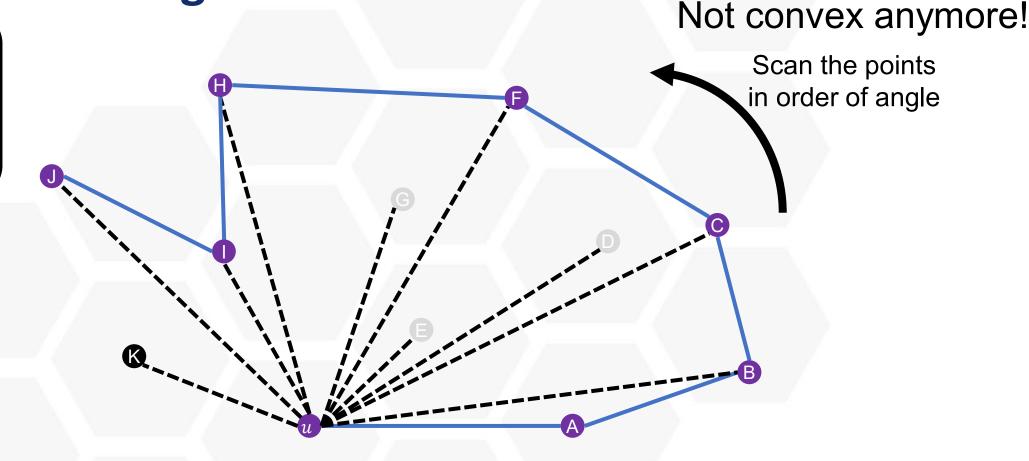




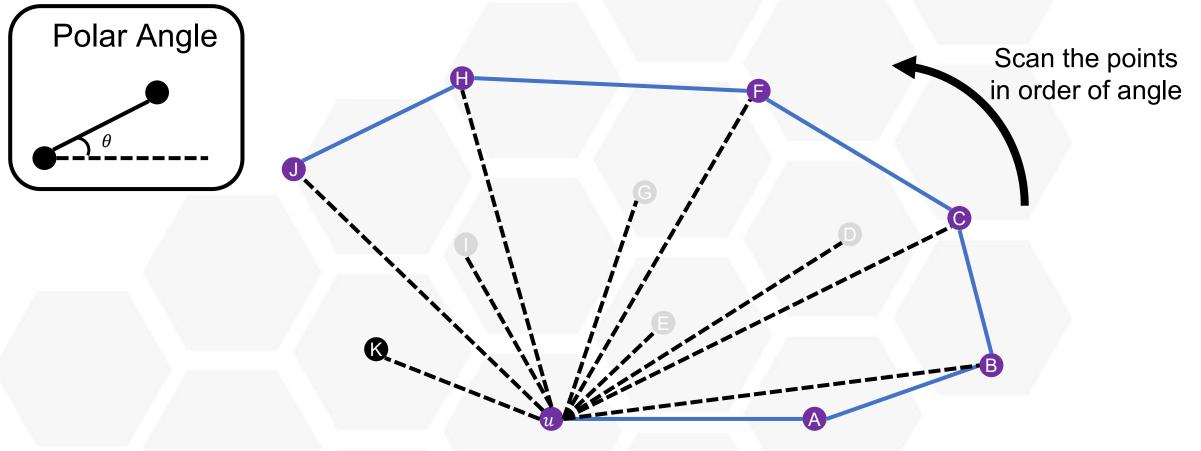
Polar Angle



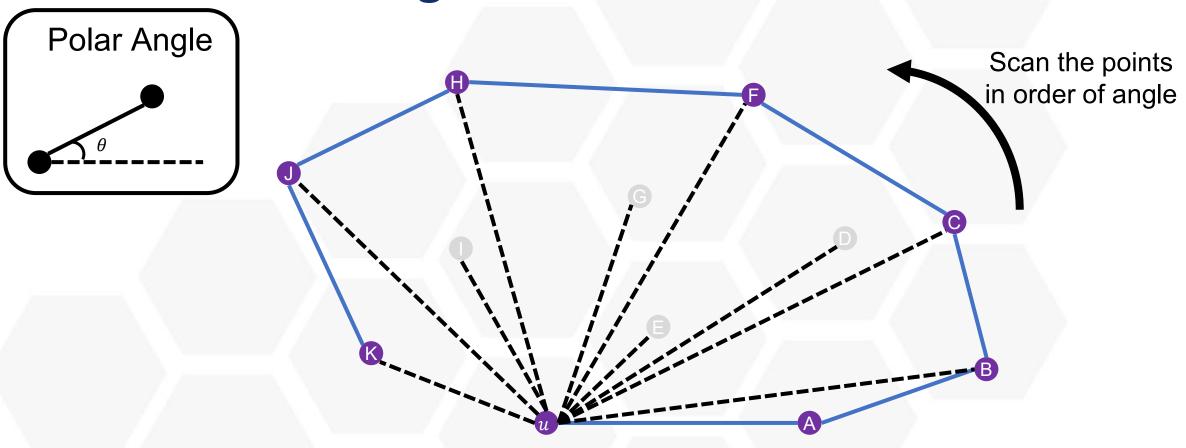




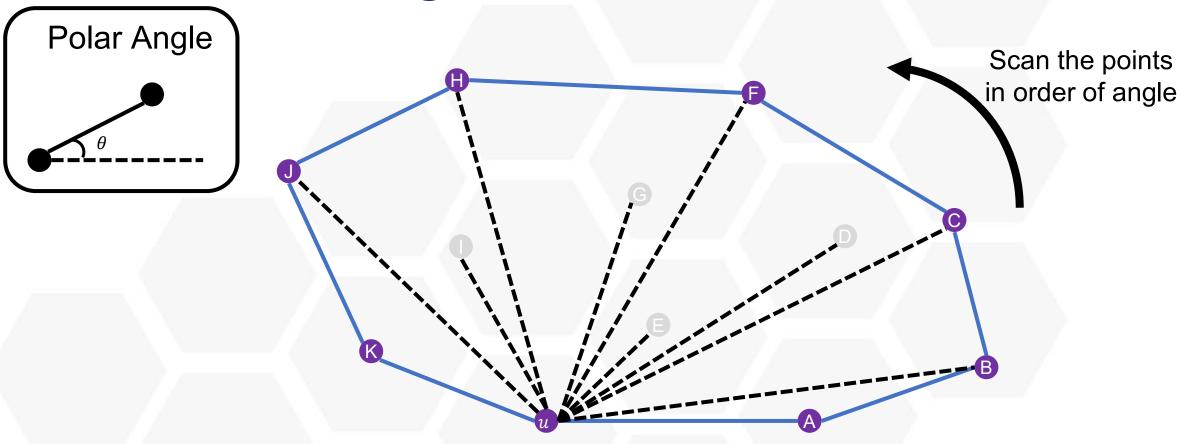






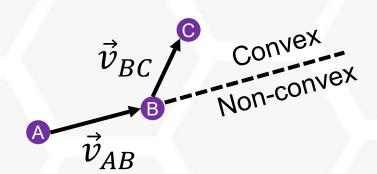






- 1. Let p_1 be the point with the smallest y-coordinate (and smallest x-coordinate if multiple points have the same minimum-y coordinate)
- 2. Add p_1 to the convex hull C (represented as an ordered list)
- 3. Sort all of the points based on their angle relative to p_1
- 4. For each of the points p_i in sorted order:
 - Try adding p_i to the convex hull C
 - If adding p_i makes \mathcal{C} non-convex, then remove the last component of \mathcal{C} and repeat this check

How to implement this?



Imagine driving from $A \rightarrow B$

- $B \rightarrow C$ is convex if need to take a "left turn" to reach C
- $B \to C$ is non-convex if need to take a "non-left turn" Decide "left turn" vs. "right turn" by computing the <u>sign</u> of the (vector) cross product between \vec{v}_{AB} and \vec{v}_{BC}



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Which data structure to use?

Need to be able to insert elements and remove in order of most-recent insertion can implement both operations in constant-time using a stack



Graham's Algorithm

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Correctness?

See Cormen 33.3



Running Time of Graham's Algorithm

- 1. Let p_1 be the point with the smallest y-coordinate (and smallest x-coordinate if multiple points have the same minimum-y coordinate)
- 2. Add p_1 to the convex hull C (represented as **a stack**)
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- O(n)
- 0(1)
- $O(n \log n)$
- 0(1)

Running time: $O(n \log n)$



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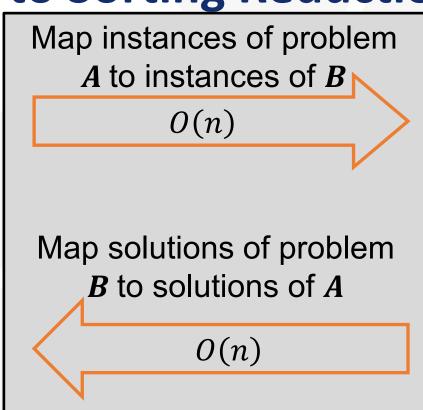
- O(n) O(1)
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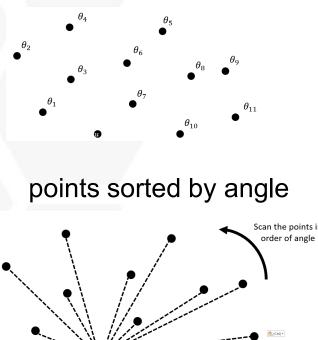
We have essentially <u>reduced</u> the problem of computing a convex hull to the problem of sorting!



Convex Hull to Sorting Reduction

convex hull convex hull





sorting

convex hull \leq sorting convex hull can be reduced to sorting in O(n) time



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Running Time of Graham's Algorithm

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Running time of Graham's algorithm: same as best sorting algorithm

Can we do better (without going through sorting)?



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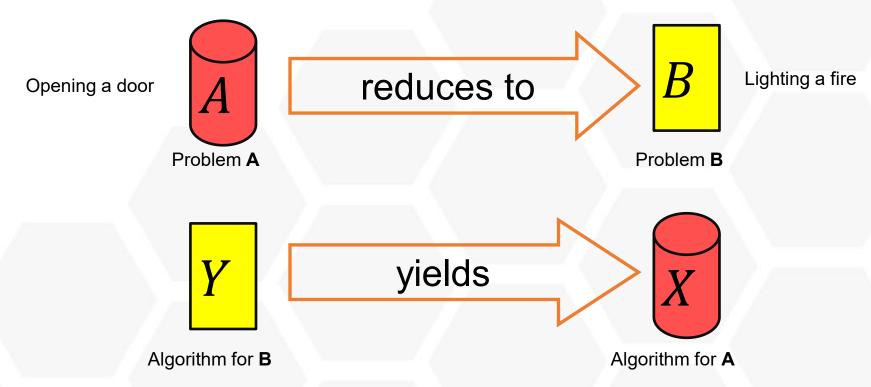
Trivial lower bound: $\Omega(n)$

m: same as best sorting algorithm

Can we do better (without going through sorting)?

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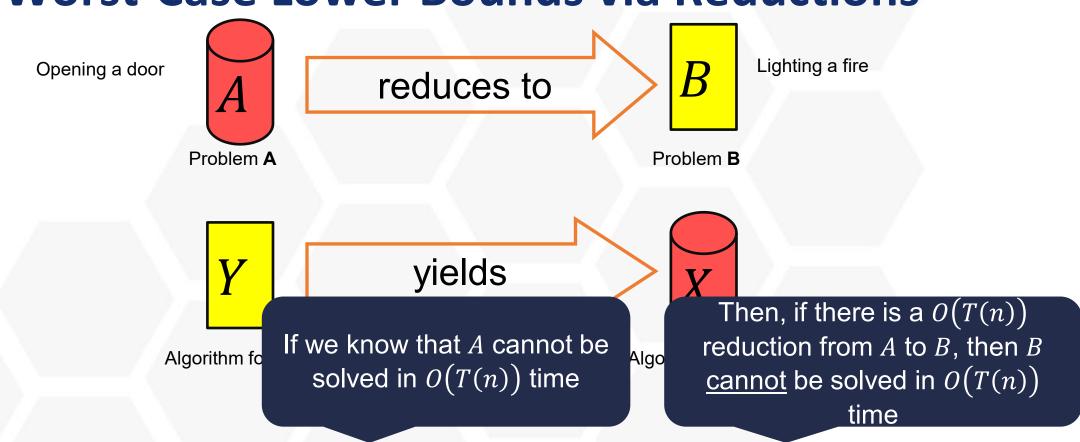
Worst-Case Lower Bounds via Reductions



Implication: A is no more difficult than B (denoted $A \leq B$)

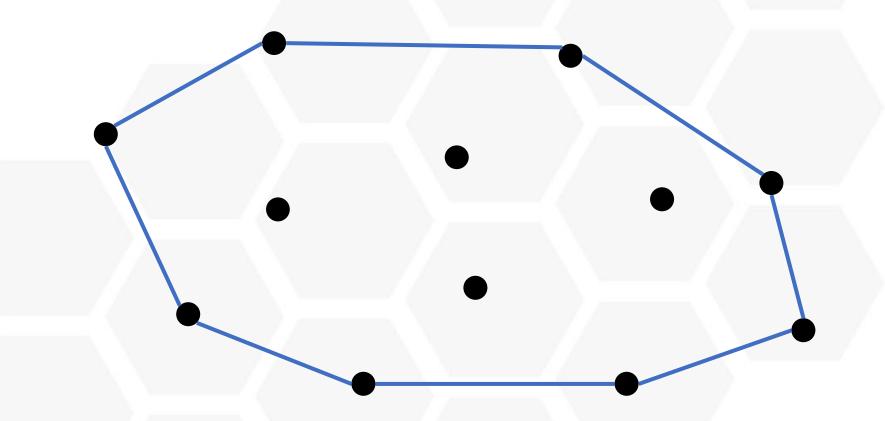


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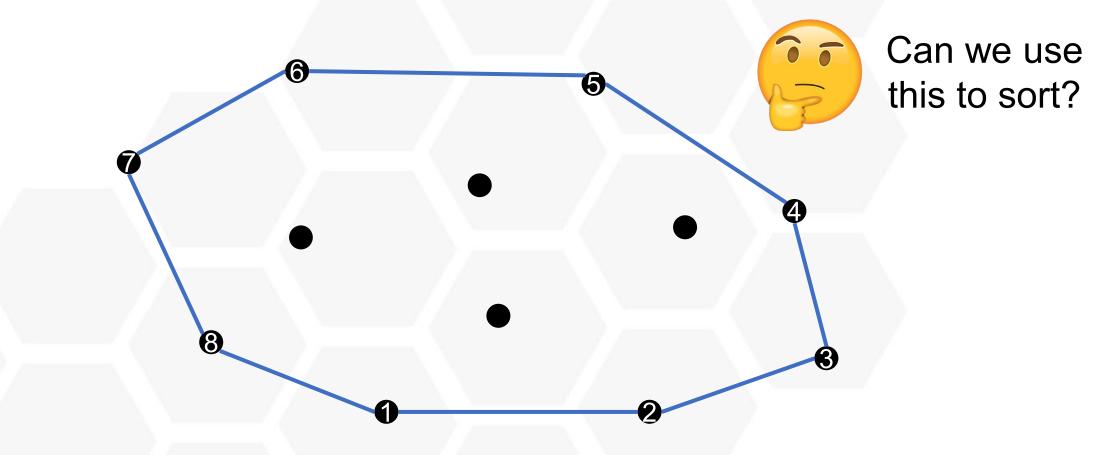
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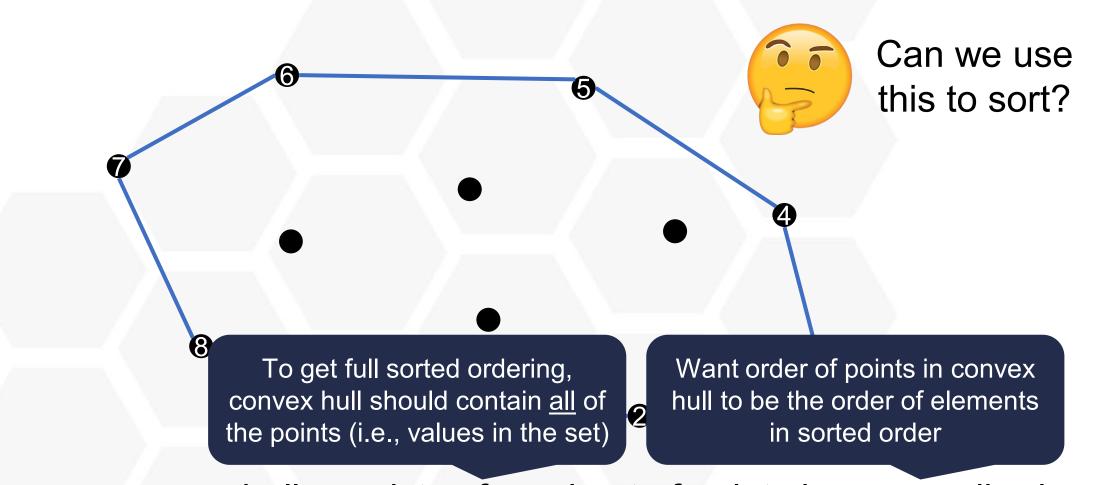
Observe: convex hull consists of a subset of points in a prescribed order



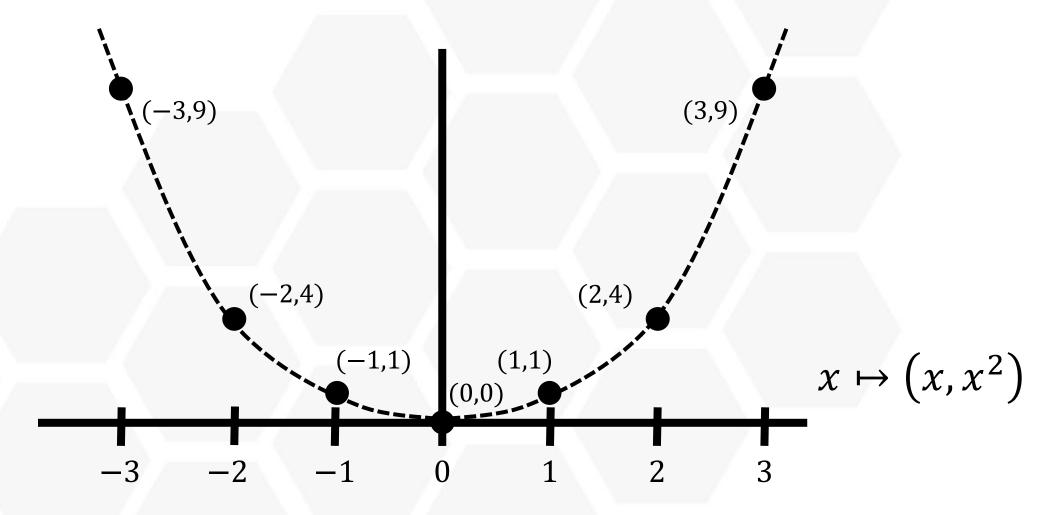


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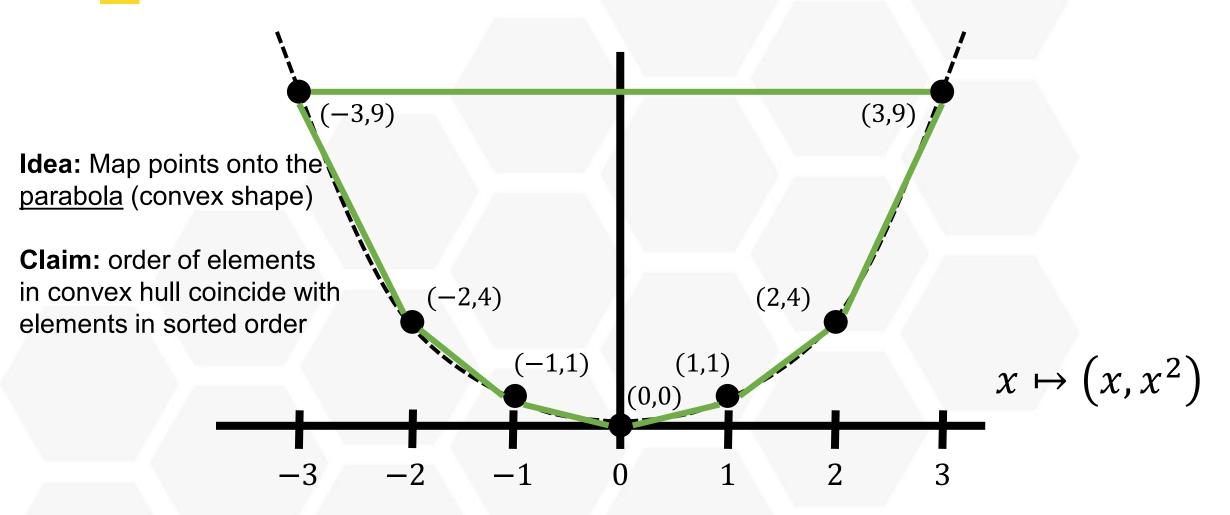


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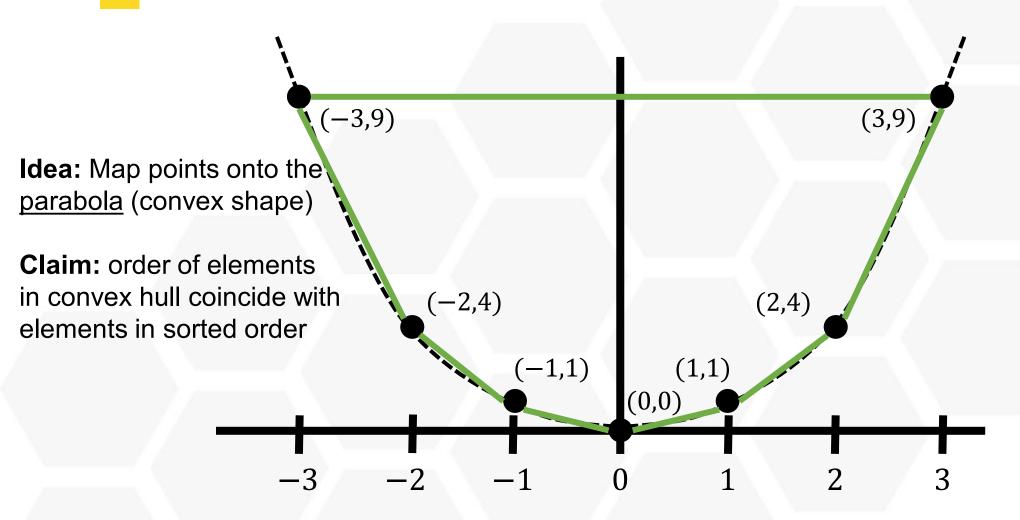
Goal: need a way to map list of (numeric) values onto a convex hull instance





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Conclusion: If we can solve convex hull, then we can sort numeric values

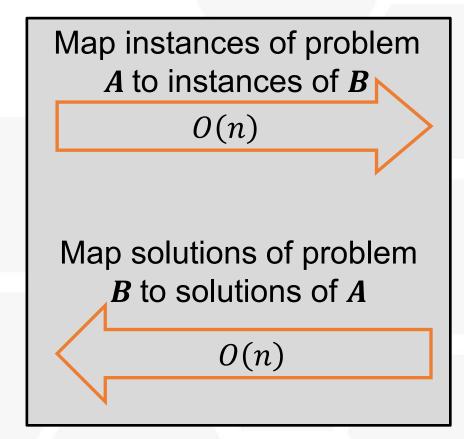


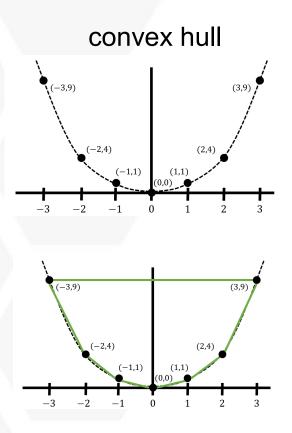
Convex Hull to Sorting Reduction

sorting

$$-2$$
 1 -3 0 2 3 -1

$$-3$$
 -2 -1 0 1 2 3

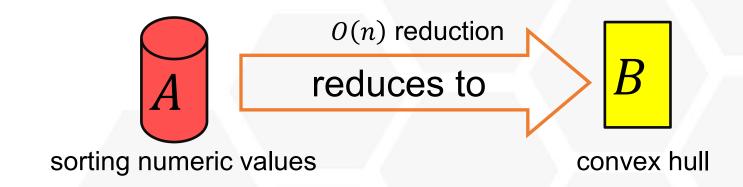




sorting numeric values \leq convex hull sorting numeric values can be reduced to convex hull in O(n) time

Lower Bound for Convex Hull





Conclusion: a lower bound for sorting translates into one for convex hull

Our lower bound for sorting: $\Omega(n \log n)$ for comparison sorts

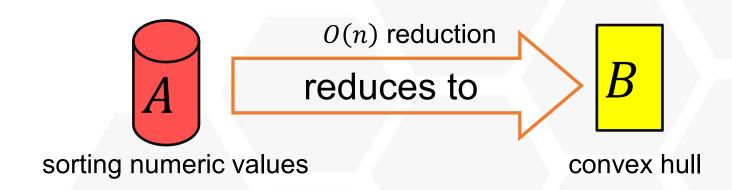
Our reduction is <u>not</u> a comparison sort algorithm, so cannot directly appeal to it

 $\Omega(n \log n)$ lower bound for sorting also holds in an "algebraic decision tree model" (i.e., decisions can be an <u>algebraic</u> function of inputs)

Implies $\Omega(n \log n)$ lower bound for computing convex hull in this model



Lower Bound for Convex Hull



Conclusion: a lower bound for sorting translates into one for convex hull

Our lower bound for sorting: $\Omega(n \log n)$ for comparison sorts

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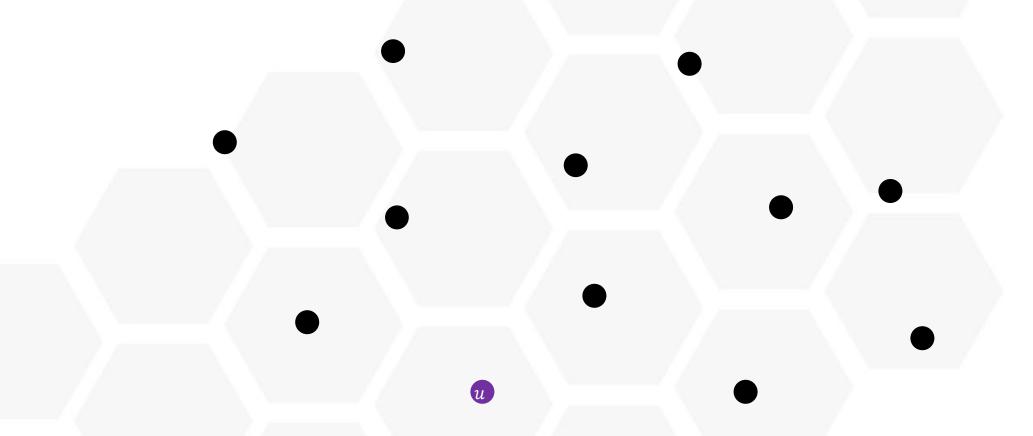
 $\Omega(n \log n)$ lower bound for (i.e., decisions can

In fact, this lower bound holds even for algorithms that just identify the set of points on the convex hull (and not necessarily their order)!

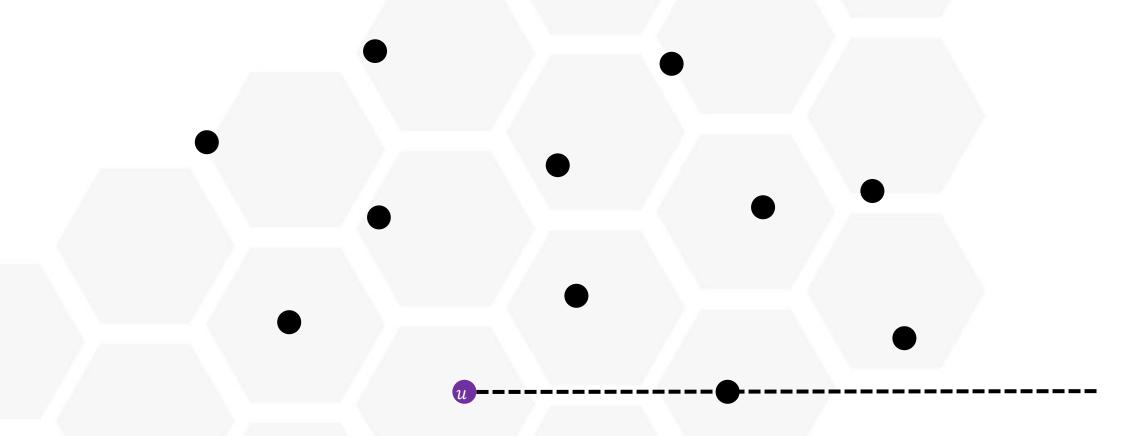
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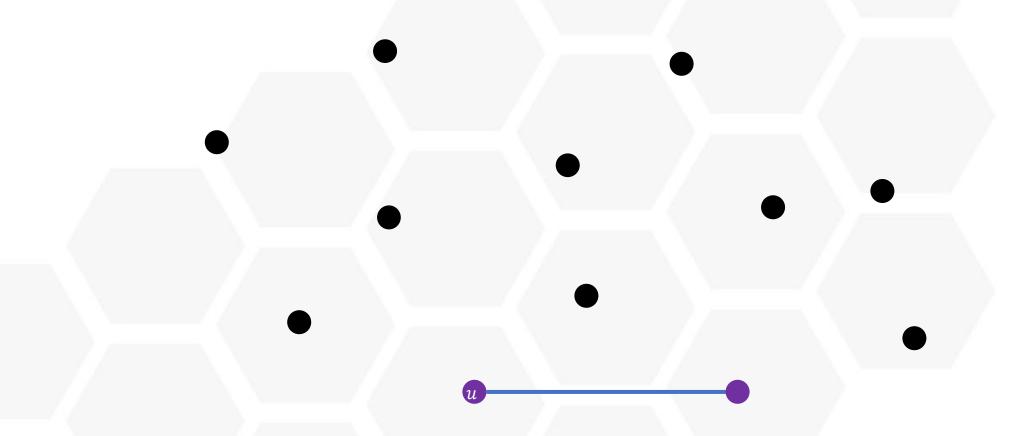


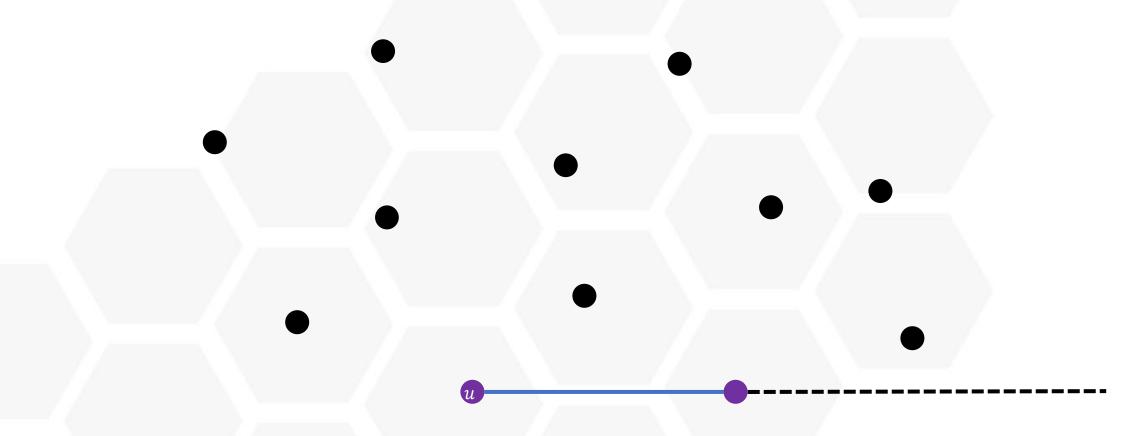


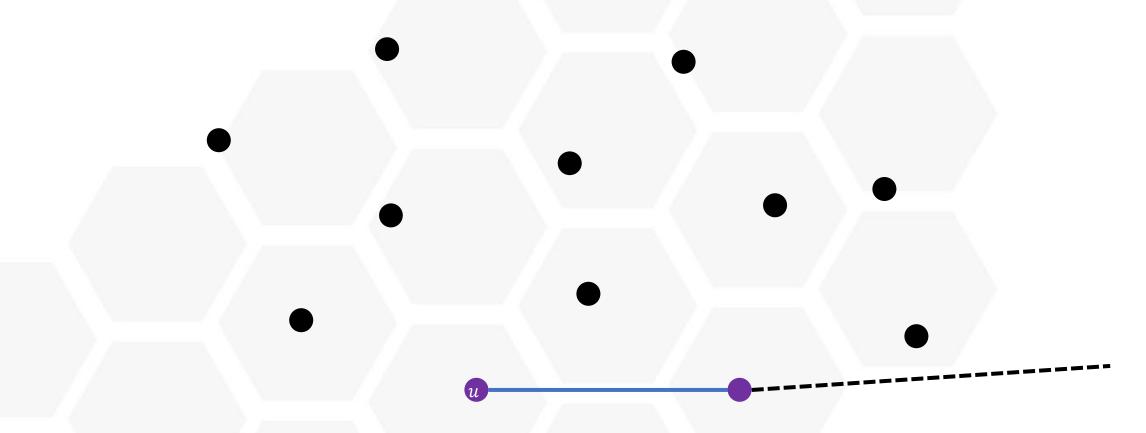


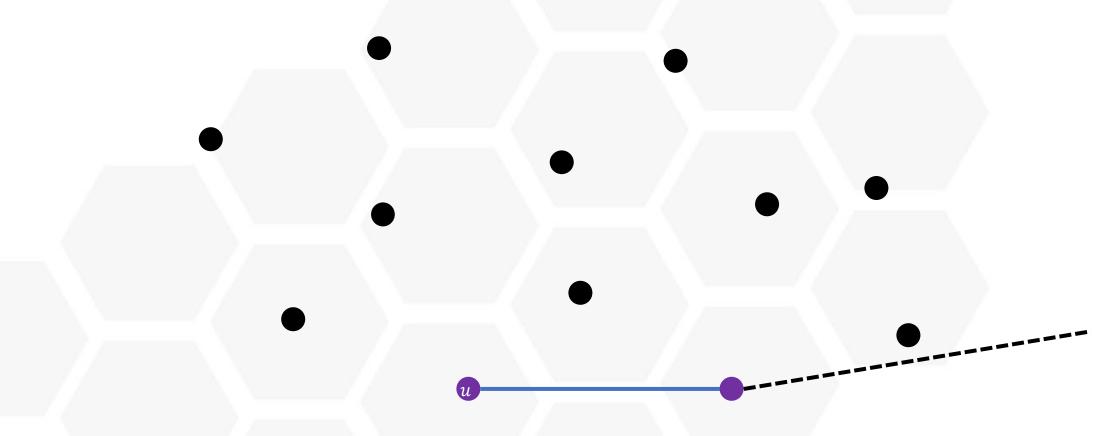


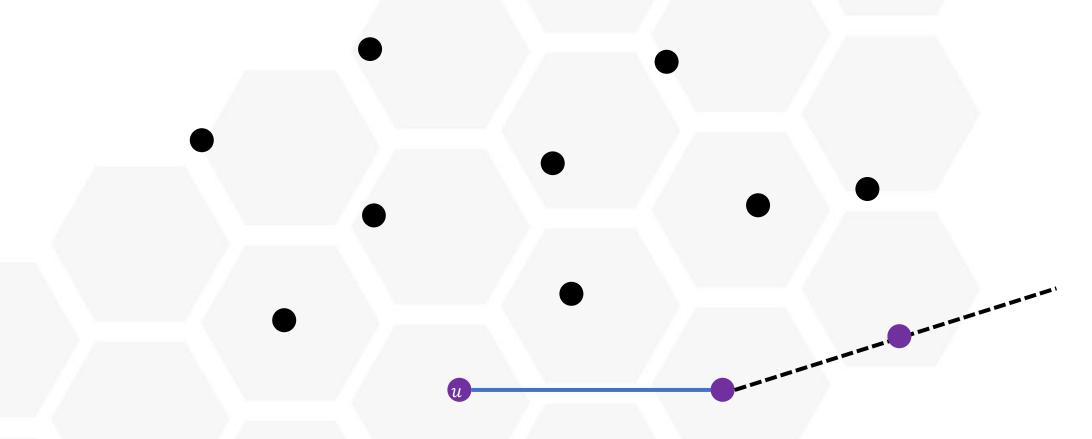




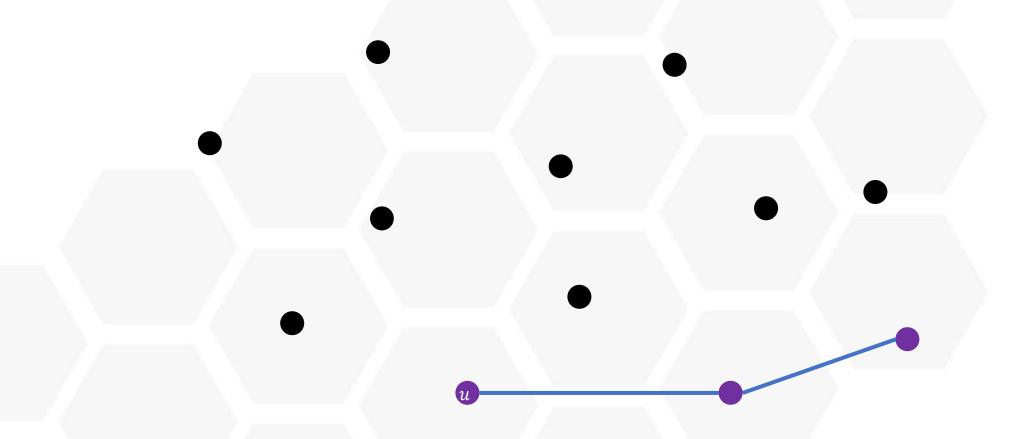


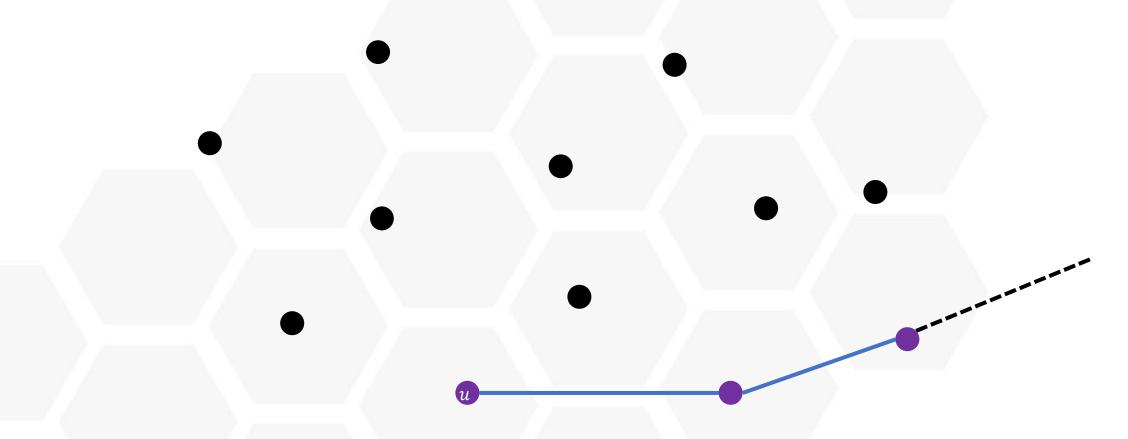




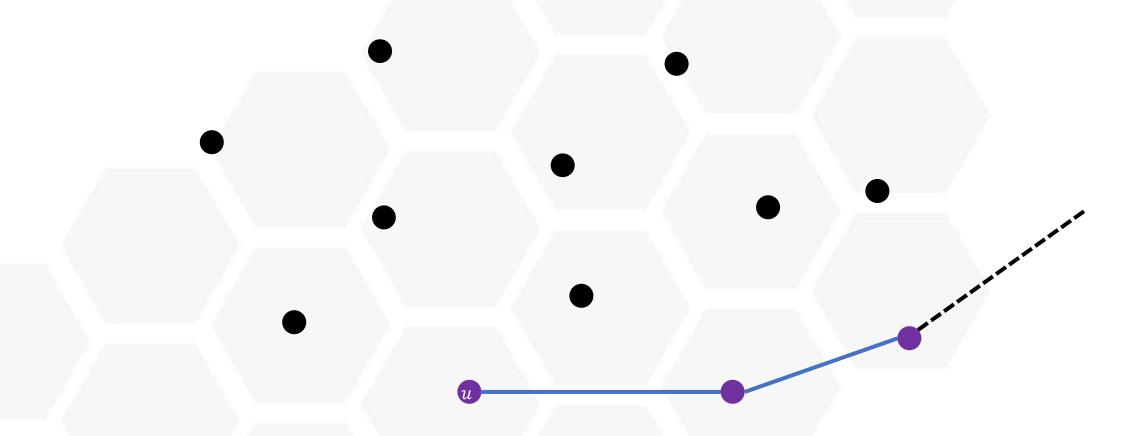


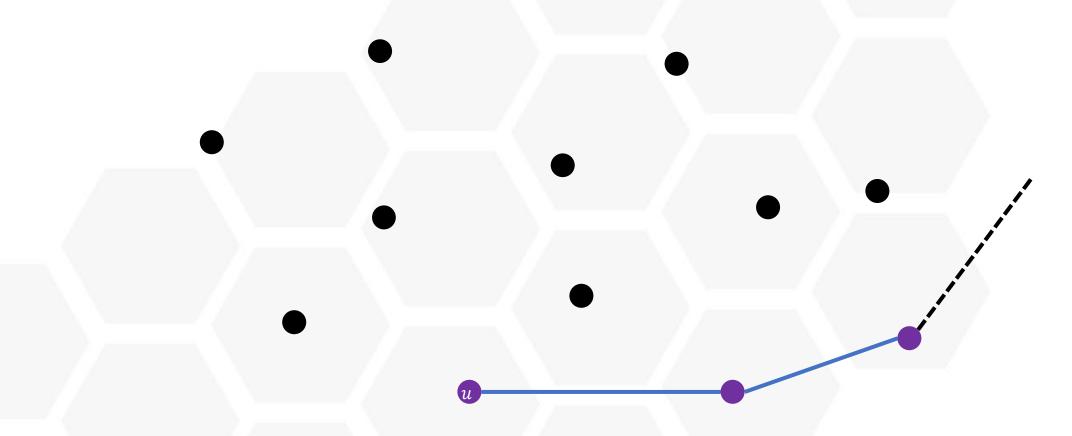




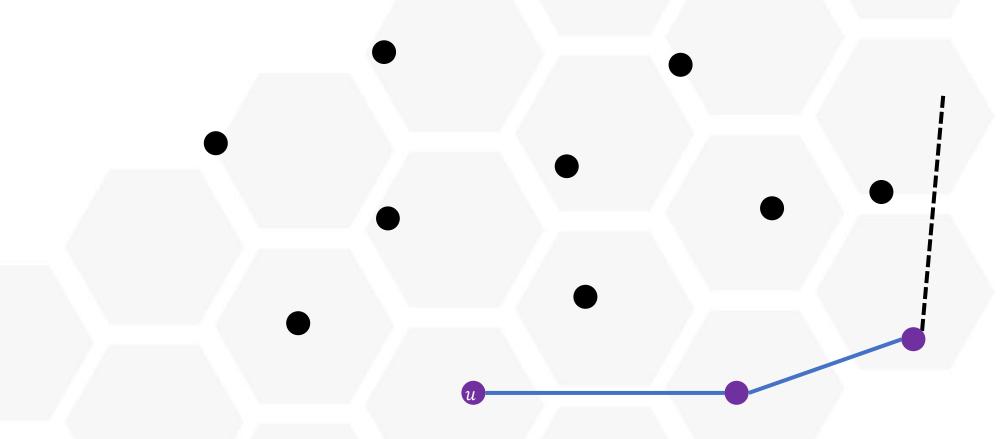




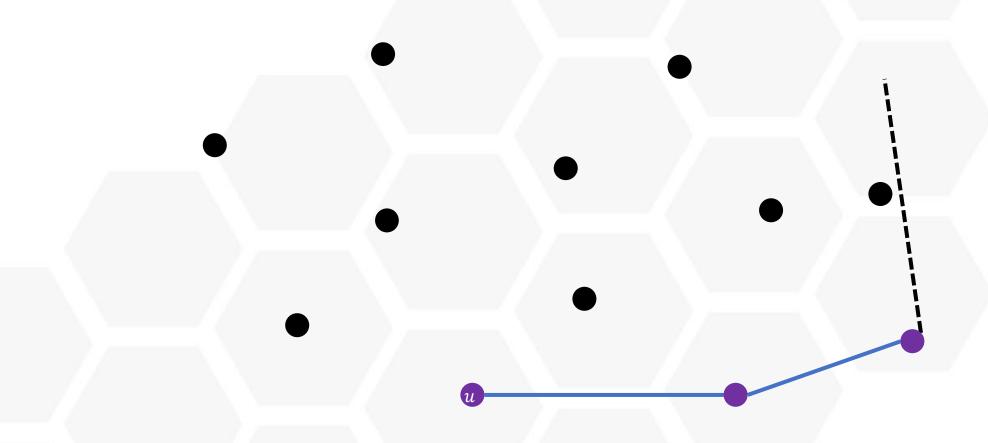


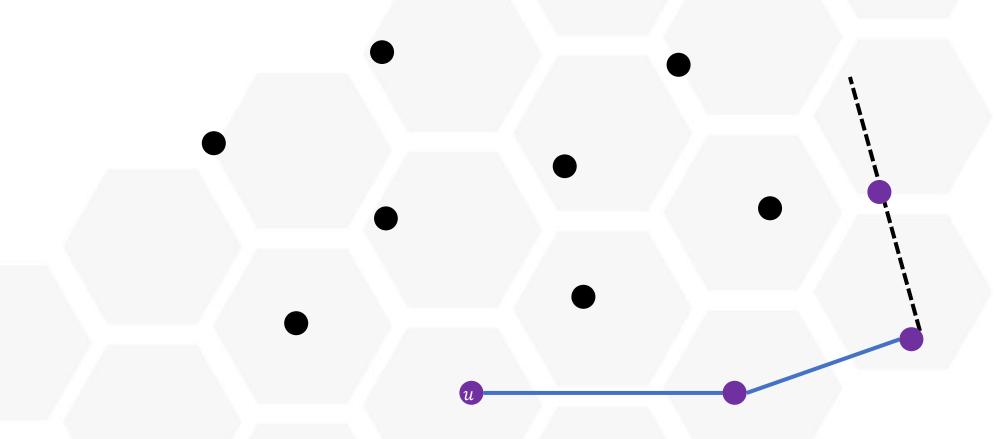




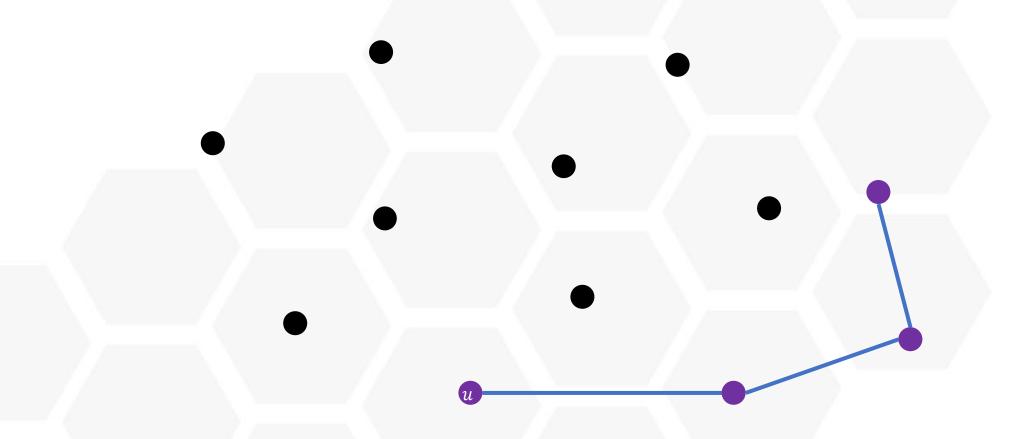


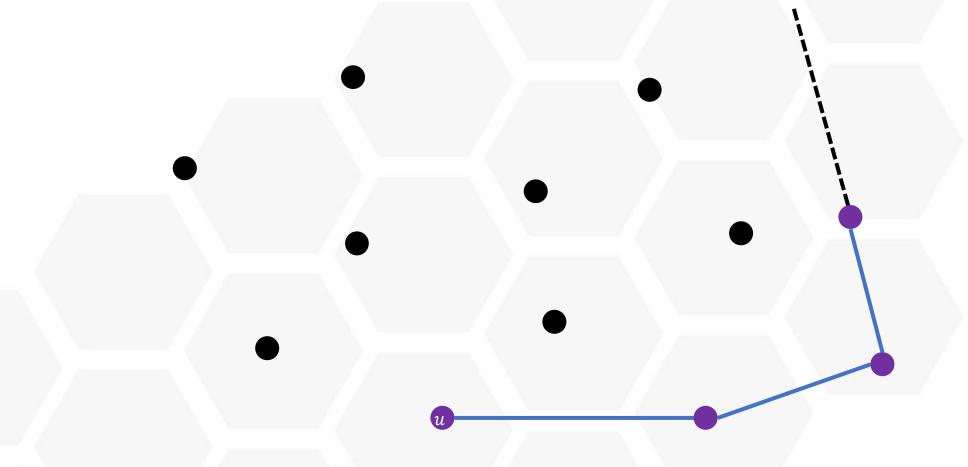


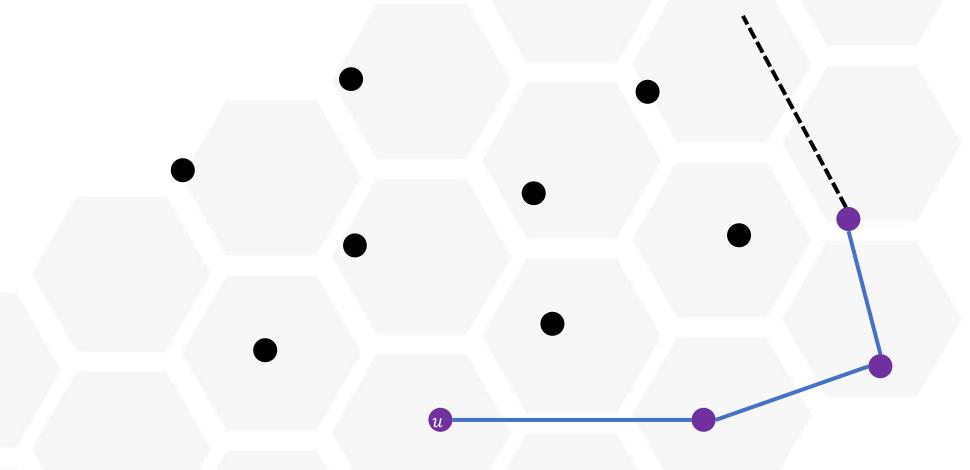




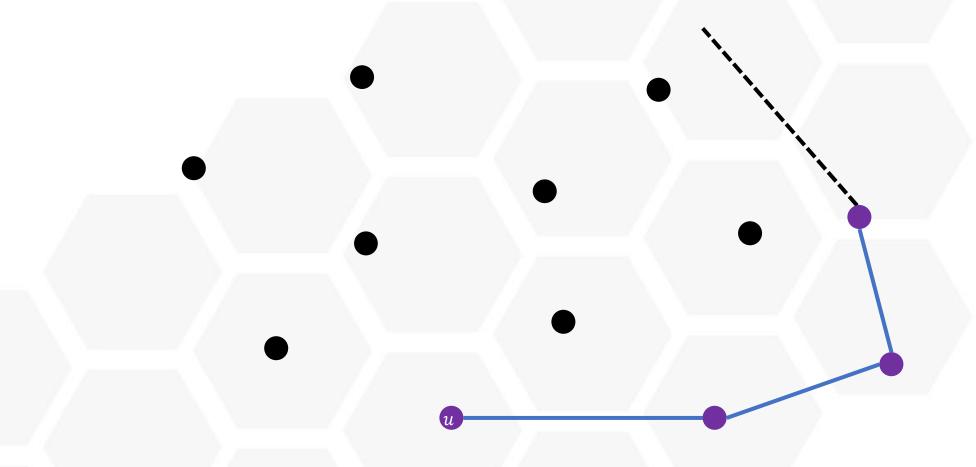




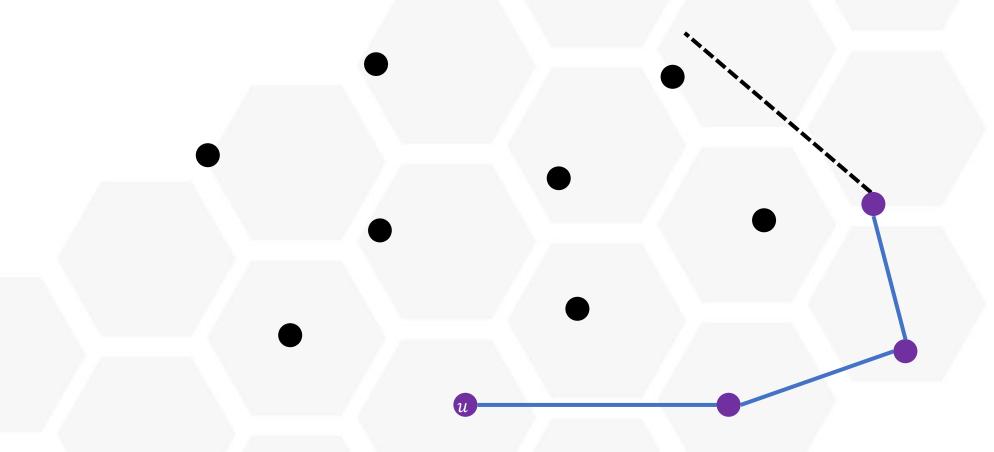




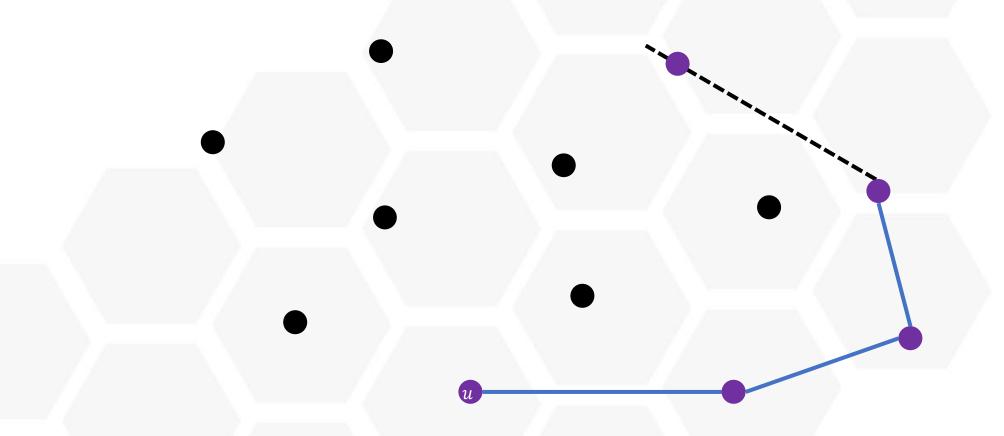




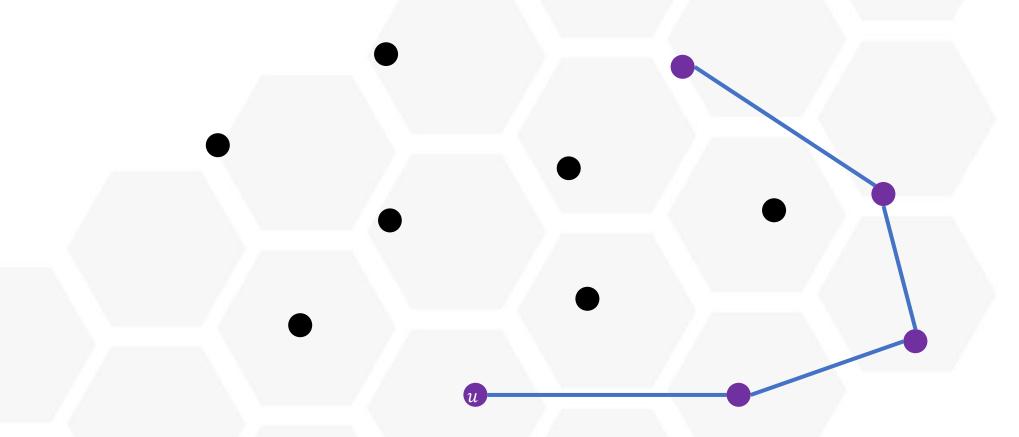




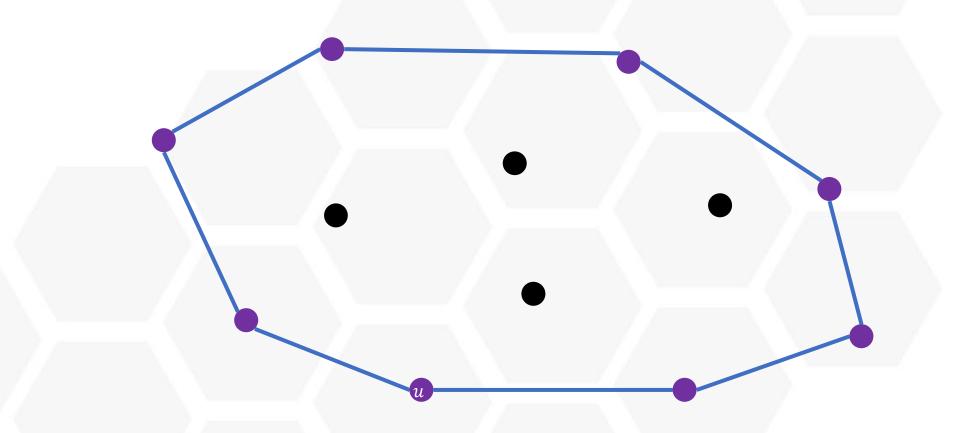




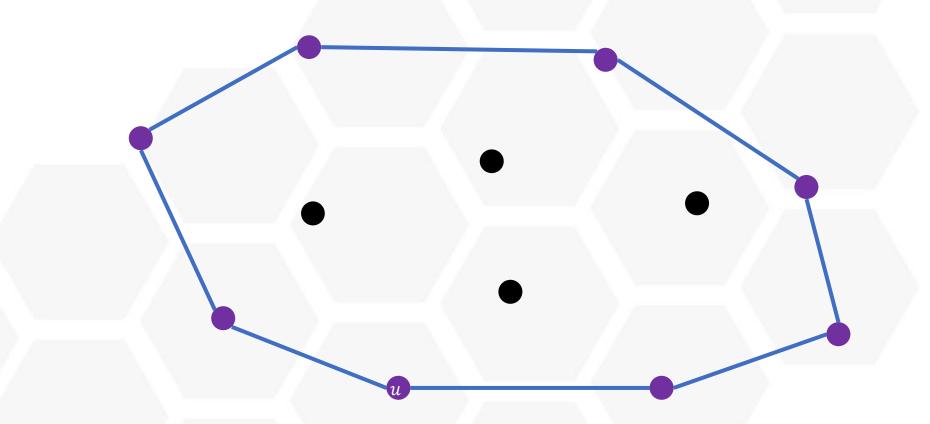










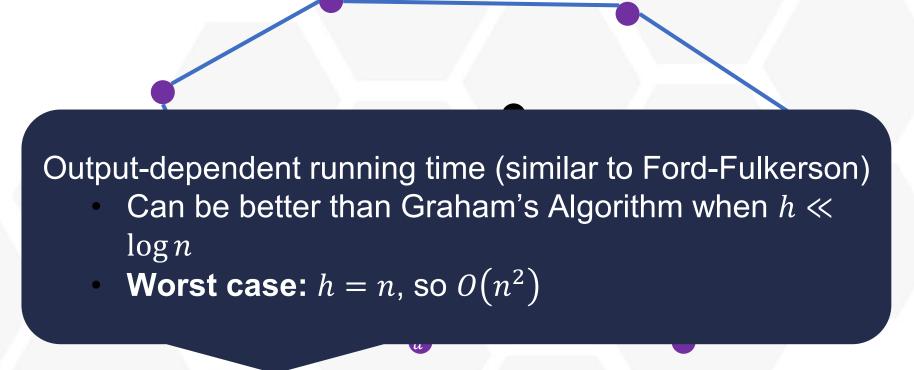


Can find the "next" point using a linear scan (i.e., point with <u>largest</u> angle)

Number of iterations: number of points on convex hull

Run time: O(nh) where h is the number of points on the convex hull





Can find the "next" point using a linear scan

Number of iterations: number of points on convex hull

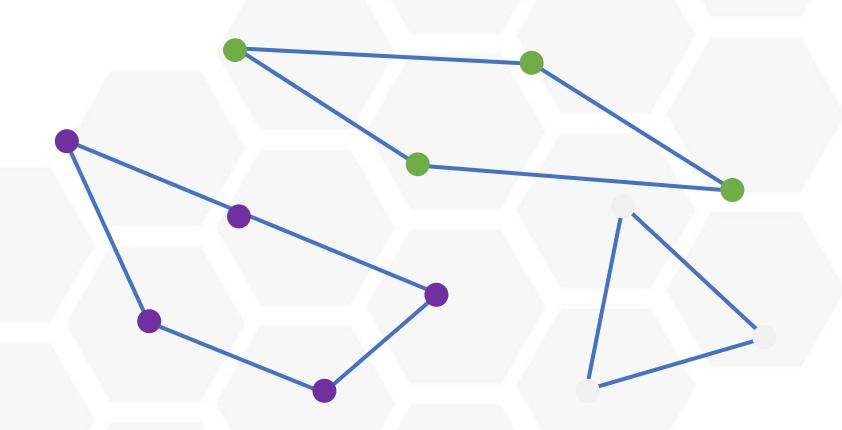
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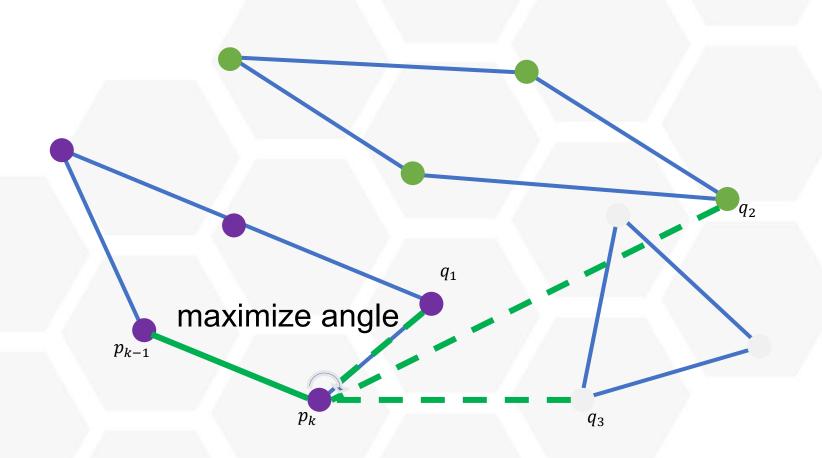
Divide into smaller subsets



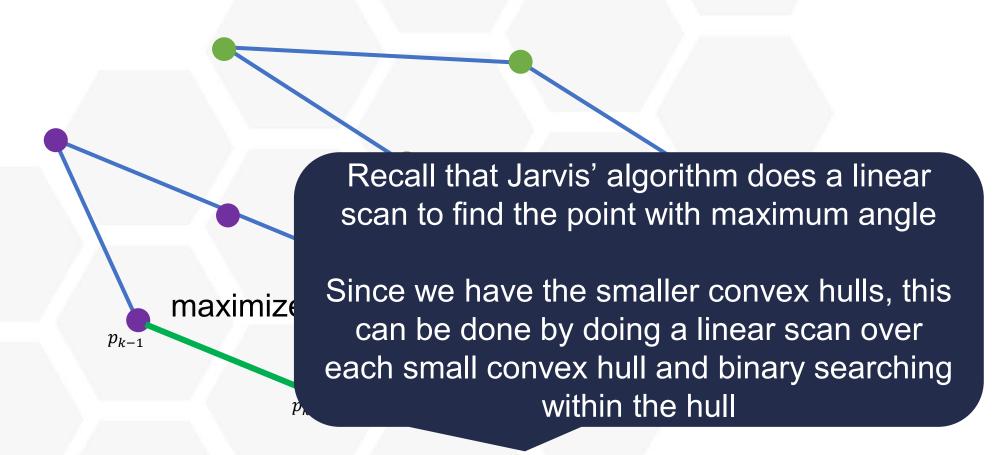


Use Graham's Algorithm to conquer the smaller subsets



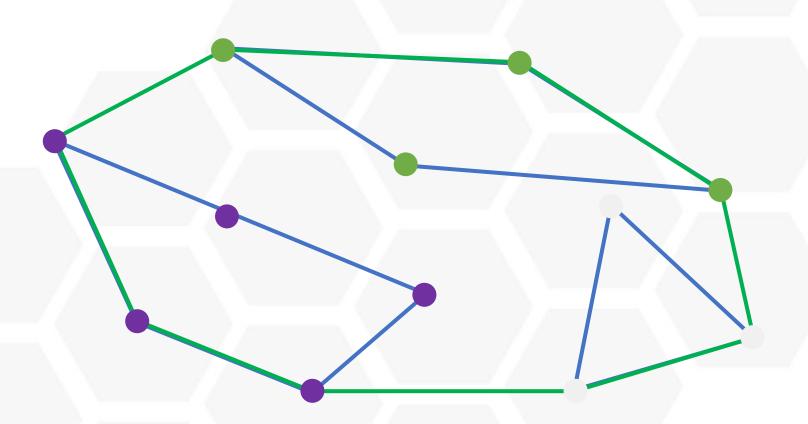


Use Jarvis' Algorithm to **combine** the solutions to the smaller subsets



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Use Jarvis' Algorithm to combine the solutions to the smaller subsets

Running time: $O(n \log h)$ – optimal!