

From Many User-Contributed Polygons To One Polygon Consensus

Fabian Feitsch

Julius-Maximilians-Universität Würzburg

July 11, 2016

The History of New York

The History of New York



The History of New York



First: Extract the buildings using image processing.

The History of New York



First: Extract the buildings using image processing.



Second: Ask users to fix the extracted polygons.

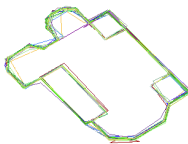
The History of New York



First: Extract the buildings using image processing.



Second: Ask users to fix the extracted polygons.



Third: Have a bunch of similar, yet different polygons.

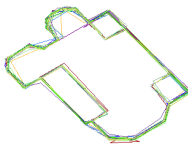
The History of New York



First: Extract the buildings using image processing.



Second: Ask users to fix the extracted polygons.



Third: Have a bunch of similar, yet different polygons.



Fourth: Which footprint was meant by the users?

Table Of Contents

A Geometry-Based Algorithm

The Pile Algorithm

Advantages and Disadvantages

Cluster-Based Algorithms

The Voting Algorithm

The MMWC Algorithm

Choice Of Parameters

Evaluation

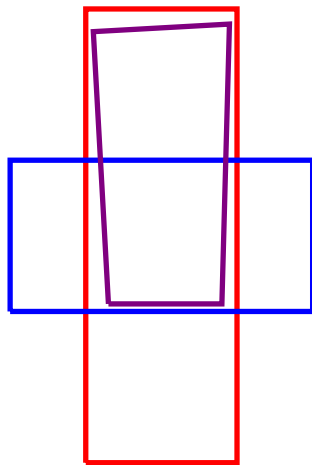
Process Of Evaluation

Semoantical Results

Brightness Results

Conclusion

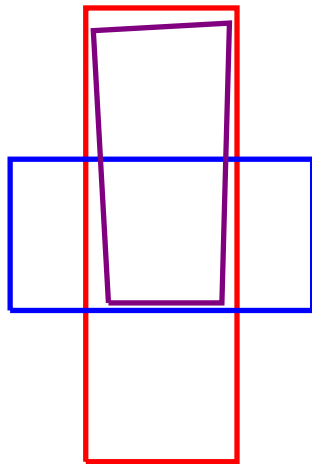
The Pile Algorithm



The Pile Algorithm

Idea

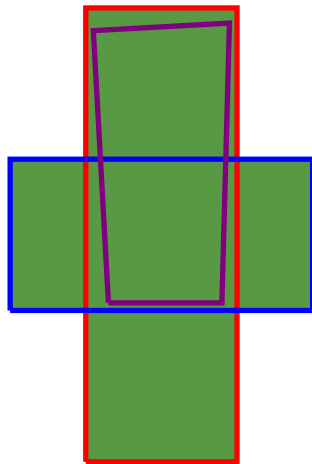
Return the area that is covered by at least k polygons.



The Pile Algorithm

Idea

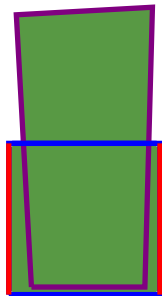
Return the area that is covered by at least k polygons.



The Pile Algorithm

Idea

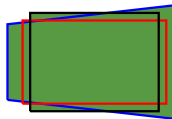
Return the area that is covered by at least k polygons.



Implications of the Pile Algorithm

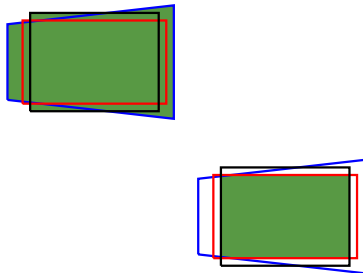
Implications of the Pile Algorithm

- ▶ Simple Interpretation



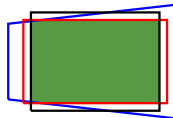
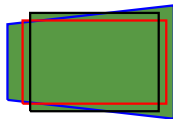
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k



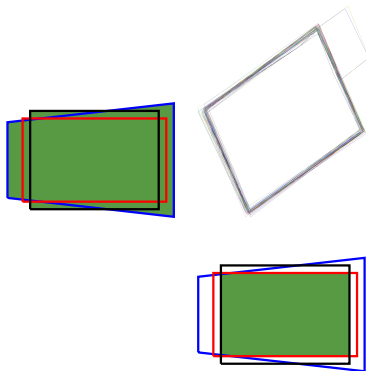
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k
- ▶ Scaling does not matter



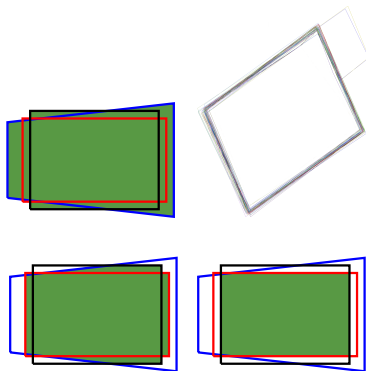
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k
- ▶ Scaling does not matter
- ▶ Implementation difficulties



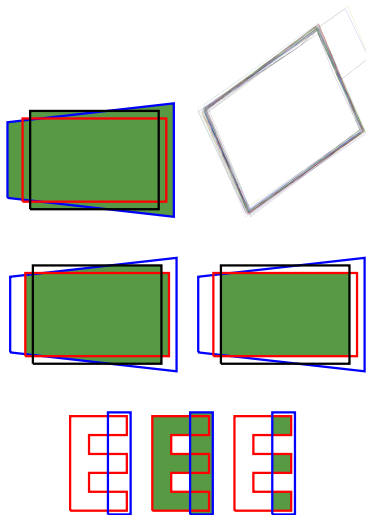
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k
- ▶ Scaling does not matter
- ▶ Implementation difficulties
- ▶ Generates too many corners



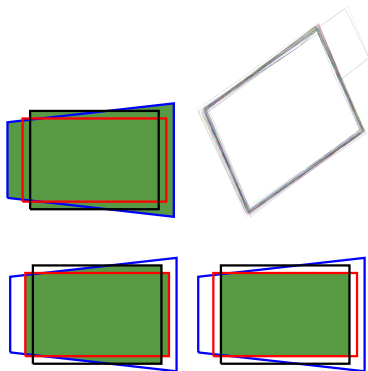
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k
- ▶ Scaling does not matter
- ▶ Implementation difficulties
- ▶ Generates too many corners
- ▶ Result is not always a simple polygon



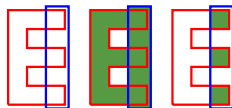
Implications of the Pile Algorithm

- ▶ Simple Interpretation
- ▶ Takes only one parameter k
- ▶ Scaling does not matter
- ▶ Implementation difficulties
- ▶ Generates too many corners
- ▶ Result is not always a simple polygon



Conclusion

The Pile algorithm is not useful for the *Building Inspector*.



Strategy of Cluster-Based Algorithms

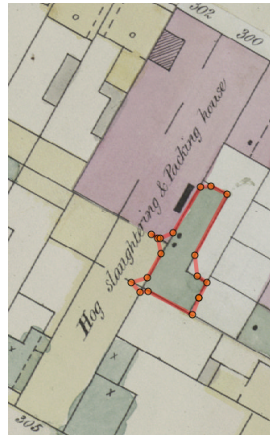
Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio
Arteaga (NYPL):

Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

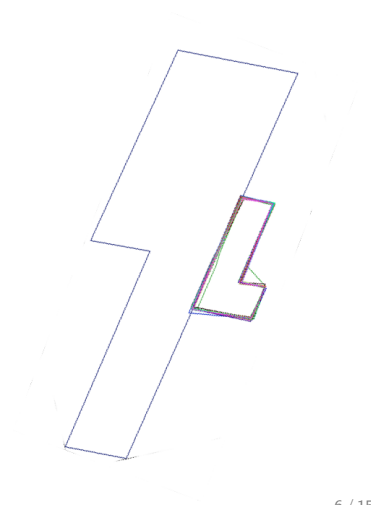
1. Outlier Removal requires parameters



Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

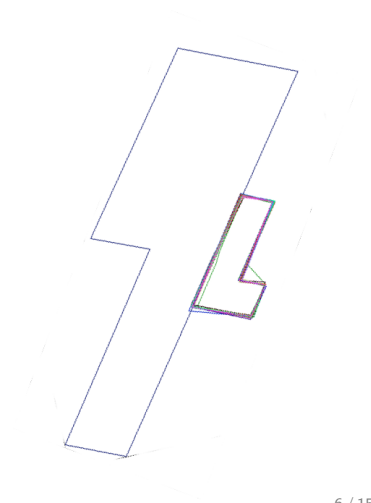
1. Outlier Removal requires parameters



Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters

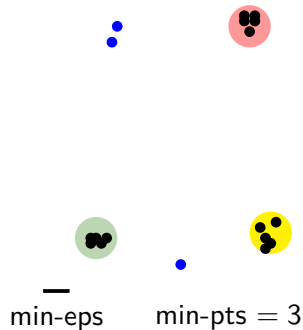


Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters

For example DBSCAN:

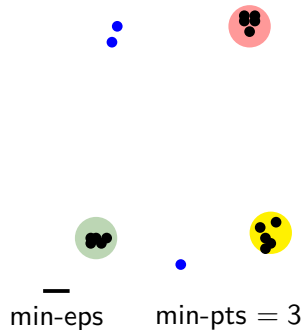


Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm

For example DBSCAN:

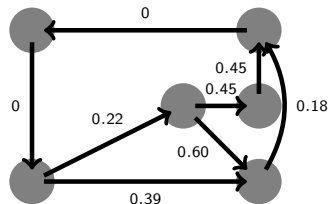


Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm

Generate graph from clusters and extract cycle.

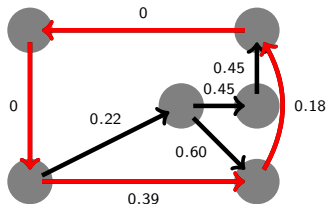


Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm
4. Translate Clusters to Polygon

Generate graph from clusters and extract cycle.



Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm
4. Translate Clusters to Polygon

Use centroids of the clusters in the circle.



Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm
4. Translate Clusters to Polygon

Use centroids of the clusters in the circle.



Claim: Either Step 1 or Step 2 can be omitted.

Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm
4. Translate Clusters to Polygon

Use centroids of the clusters in the circle.



Claim: Either Step 1 or Step 2 can be omitted.
To be shown later ...

Strategy of Cluster-Based Algorithms

Four steps derived from Mauricio Arteaga (NYPL):

1. Outlier Removal requires parameters
2. Clustering of Corners requires parameters
3. Apply actual Algorithm ← Now!
4. Translate Clusters to Polygon

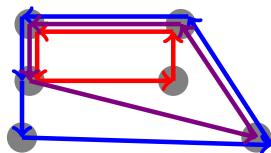
Use centroids of the clusters in the circle.



Claim: Either Step 1 or Step 2 can be omitted.
To be shown later ...

The Voting Algorithm

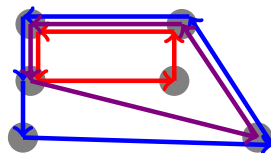
The Voting Algorithm



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

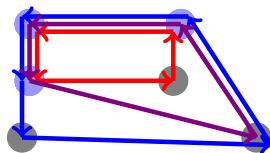
1. Find cluster c with most corners.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

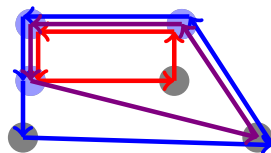
1. Find cluster c with most corners.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

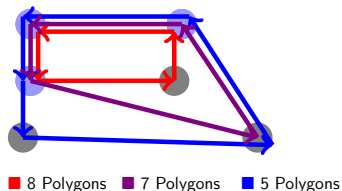
1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

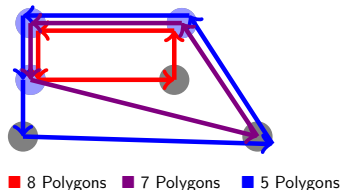
The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.



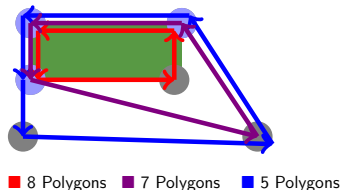
The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.



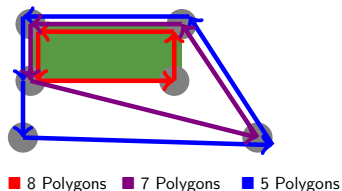
The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.



The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.



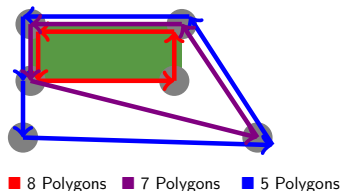
Unfortunately, there are subtleties:

The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.

Unfortunately, there are subtleties:

- ▶ Orientation of Polygons

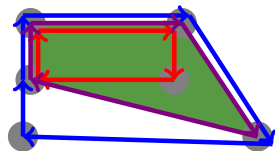


The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.

Unfortunately, there are subtleties:

- ▶ Orientation of Polygons



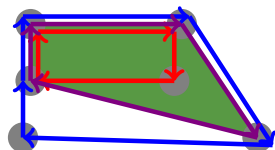
■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.

Unfortunately, there are subtleties:

- ▶ Orientation of Polygons
- ▶ Result can be arbitrarily bad ...



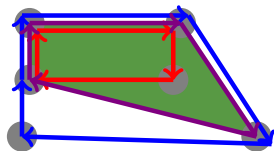
■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.

Unfortunately, there are subtleties:

- ▶ Orientation of Polygons
- ▶ Result can be arbitrarily bad ...
- ▶ ... or not existent in the input.



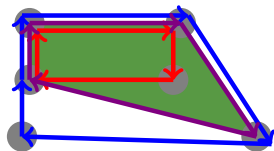
■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

The Voting Algorithm

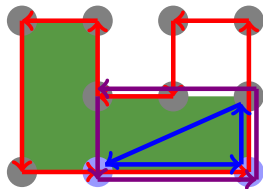
1. Find cluster c with most corners.
2. Select neighbor of c which most users agree with.
3. Proceed until cycle is found.
4. Return that cycle.

Unfortunately, there are subtleties:

- ▶ Orientation of Polygons
- ▶ Result can be arbitrarily bad ...
- ▶ ... or not existent in the input.

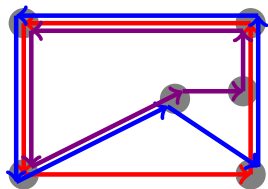


■ 8 Polygons ■ 7 Polygons ■ 5 Polygons



Minimum Mean Weight Cycle Algorithm

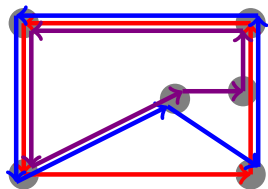
Minimum Mean Weight Cycle Algorithm



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

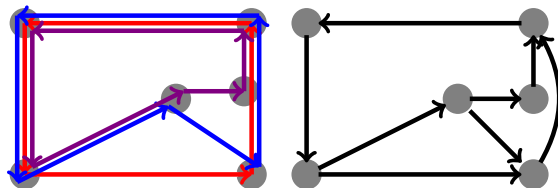
1. Consider input as directed, weighted graph.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

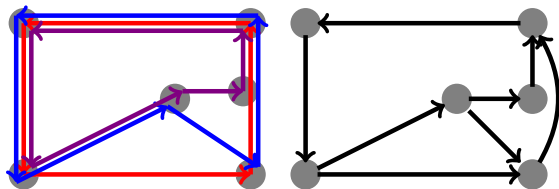
1. Consider input as directed, weighted graph.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

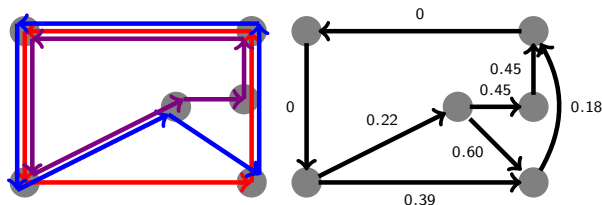
1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

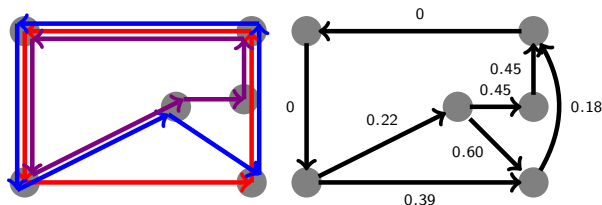
1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

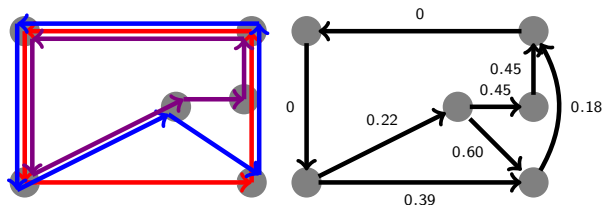
1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.
3. Find cycle with minimum mean weight in the graph.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

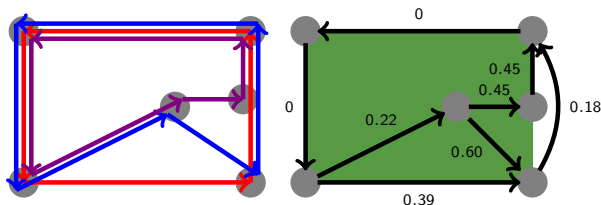
1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.
3. Find cycle with minimum mean weight in the graph.
4. Return that cycle and translate it to a polygon.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

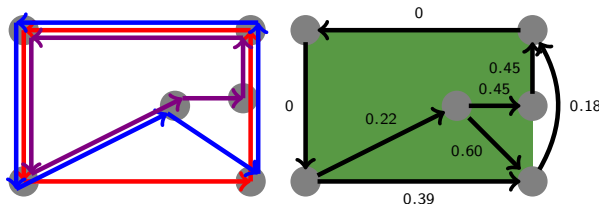
1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.
3. Find cycle with minimum mean weight in the graph.
4. Return that cycle and translate it to a polygon.



■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Minimum Mean Weight Cycle Algorithm

1. Consider input as directed, weighted graph.
2. Let k be the count of edges between c_1 and c_2 .
 Then the edge (c_1, c_2) has the weight $w = -\log(\frac{k}{n})$.
3. Find cycle with minimum mean weight in the graph.
4. Return that cycle and translate it to a polygon.



*No more
 orientation-
 dependent!*

■ 8 Polygons ■ 7 Polygons ■ 5 Polygons

Choice Of Parameters

Choice Of Parameters

Problem: How to find a good min-eps for clustering?

Choice Of Parameters

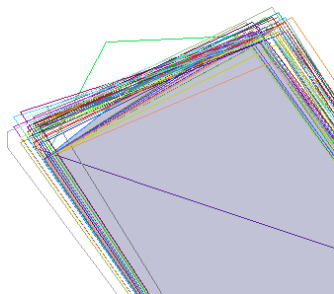
Problem: How to find a good min-eps for clustering?

Solution so far: Trial and Error

Choice Of Parameters

Problem: How to find a good min-eps for clustering?

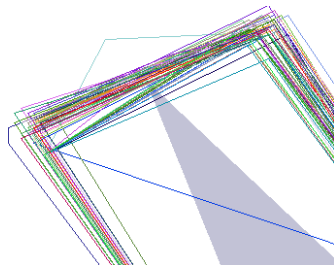
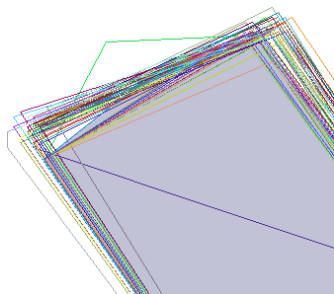
Solution so far: Trial and Error



Choice Of Parameters

Problem: How to find a good min-eps for clustering?

Solution so far: Trial and Error

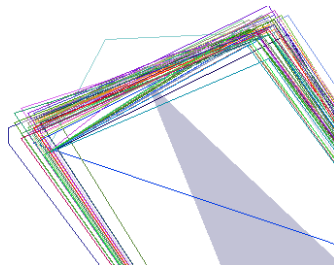
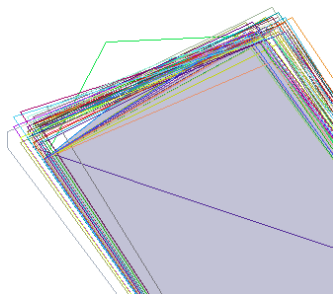


Choice Of Parameters

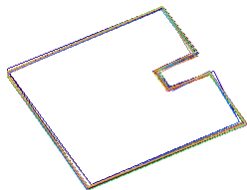
Problem: How to find a good min-eps for clustering?

Solution so far: Trial and Error

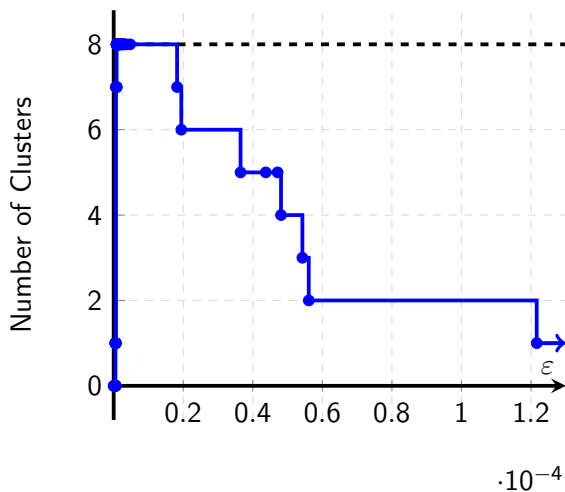
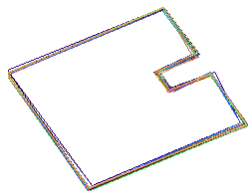
Hope: Find min-eps automatically



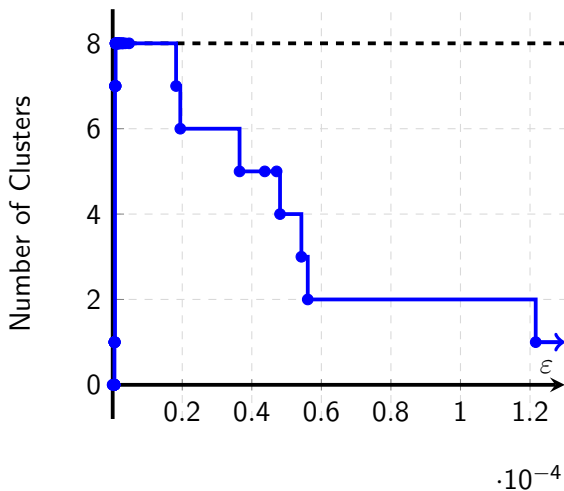
From an Observation to a Heuristic



From an Observation to a Heuristic

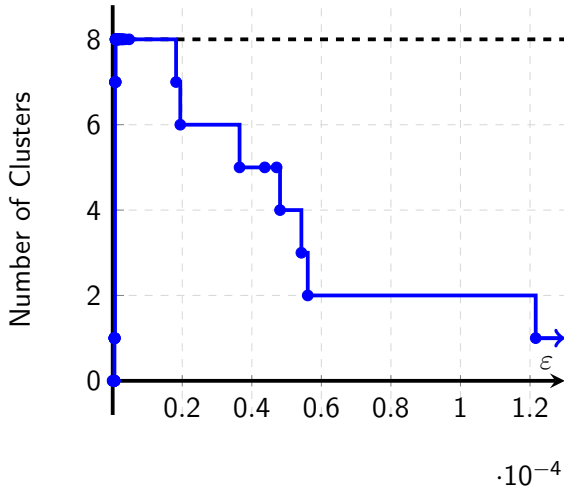


From an Observation to a Heuristic



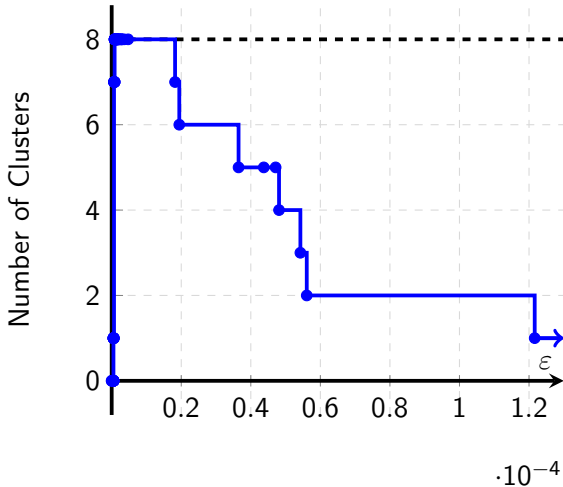
From an Observation to a Heuristic

- Calculate median.



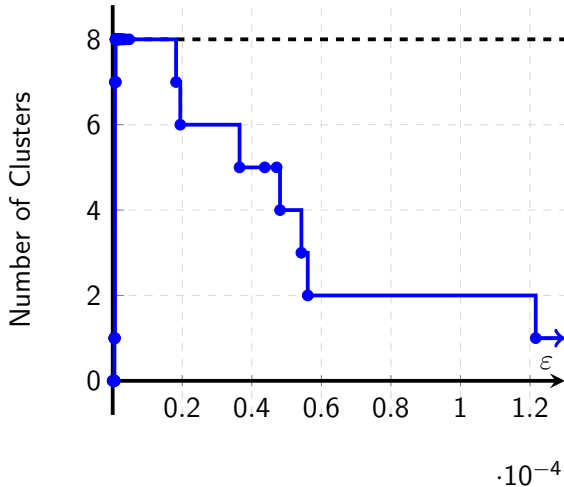
From an Observation to a Heuristic

- ▶ Calculate median.
- ▶ Allow only clusters of size $n/2$.



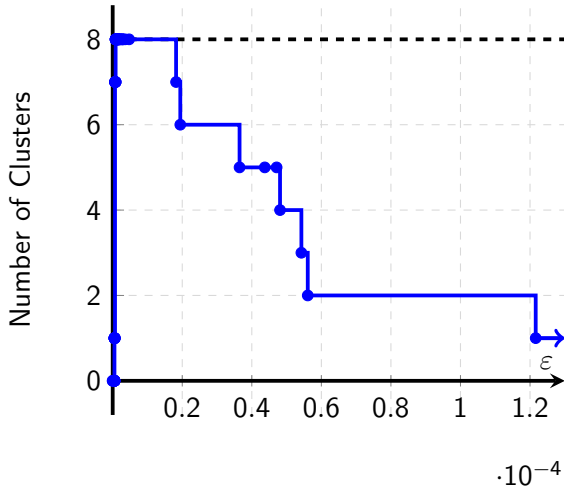
From an Observation to a Heuristic

- ▶ Calculate median.
- ▶ Allow only clusters of size $n/2$.
- ▶ Select longest plateau.



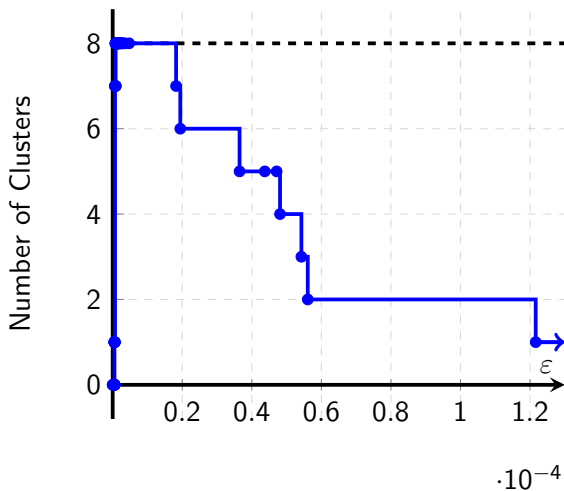
From an Observation to a Heuristic

- ▶ Calculate median.
- ▶ Allow only clusters of size $n/2$.
- ▶ Select longest plateau.
- ▶ Use Semi-Dynamic-Sets.



From an Observation to a Heuristic

- ▶ Calculate median.
- ▶ Allow only clusters of size $n/2$.
- ▶ Select longest plateau.
- ▶ Use Semi-Dynamic-Sets.
- ▶ Running time $\mathcal{O}(n^2 \log n)$.



Evaluation Process

Evaluation Process

Sources

Evaluation Process

Sources
detected,

Evaluation Process

Sources

detected, user,

Evaluation Process

Sources

detected, user,
mmwc-autoeps,

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw,

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps,

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw,

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of
buildings.

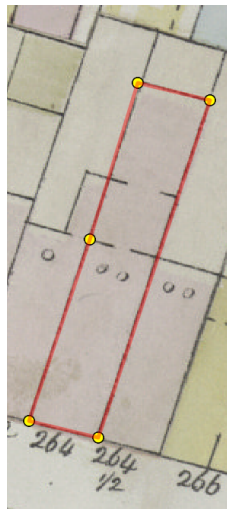
Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of
buildings.



Evaluation Process

Sources

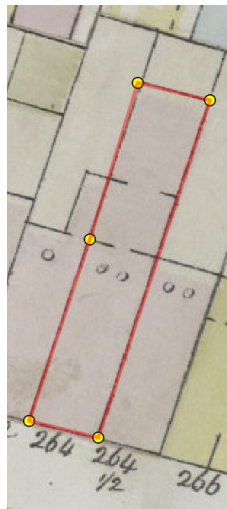
detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of buildings.

Accuracy

Extract the average brightness of the pixels *under* the polygon edges automatically. The lower the better!



Evaluation Process

Sources

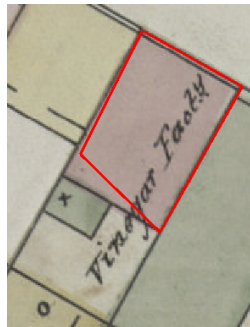
detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of
buildings.

Accuracy

Extract the average brightness of the pixels
under the polygon edges automatically. The
lower the better!



Value: 0.48

Evaluation Process

Sources

detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of
buildings.

Accuracy

Extract the average brightness of the pixels
under the polygon edges automatically. The
lower the better!



Value: 0.38

Evaluation Process

Sources

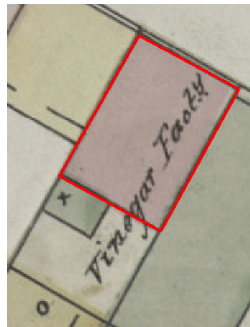
detected, user,
mmwc-autoeps, mmwc-raw, mmwc-clean,
voting-autoeps, voting-raw, voting-clean

Semantics

Check if the polygons fit to footprints of
buildings.

Accuracy

Extract the average brightness of the pixels
under the polygon edges automatically. The
lower the better!

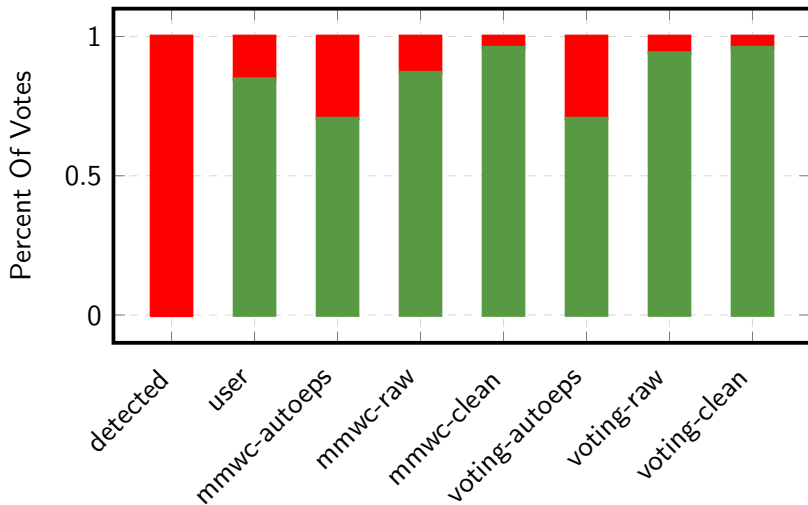


Value: 0.36

Semantical Results

Semantical Results

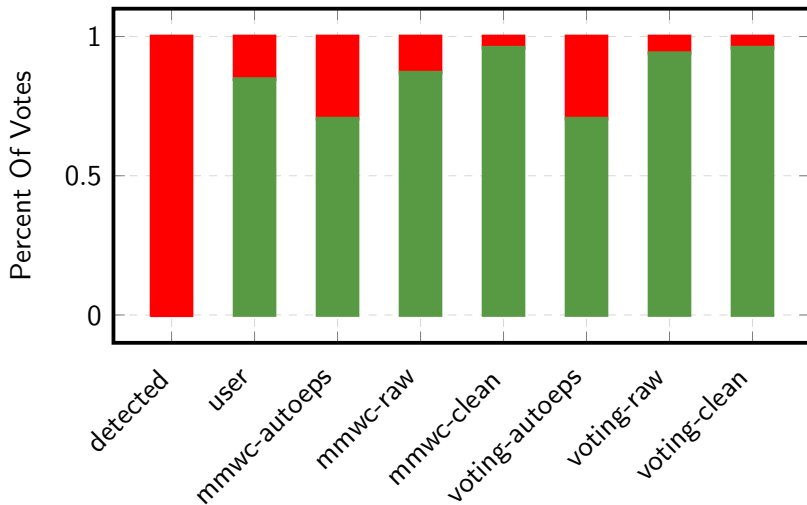
■ Yes ■ No



Semantical Results

■ Yes ■ No

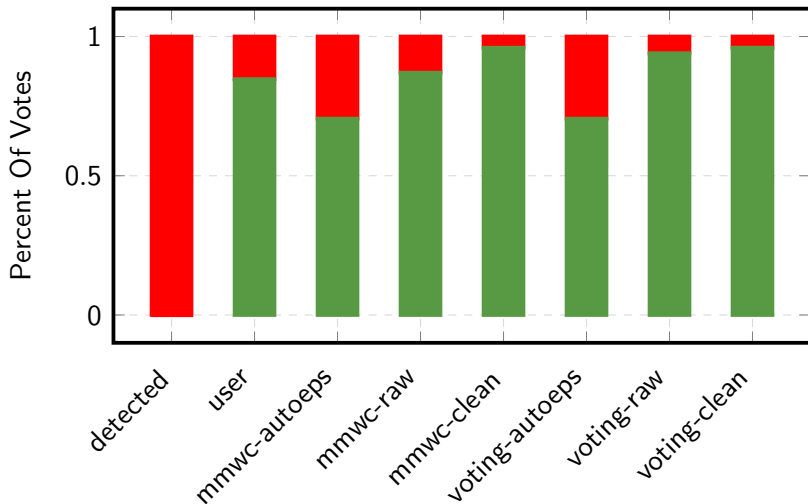
MMWC was not better than Voting!



Semantical Results

■ Yes ■ No

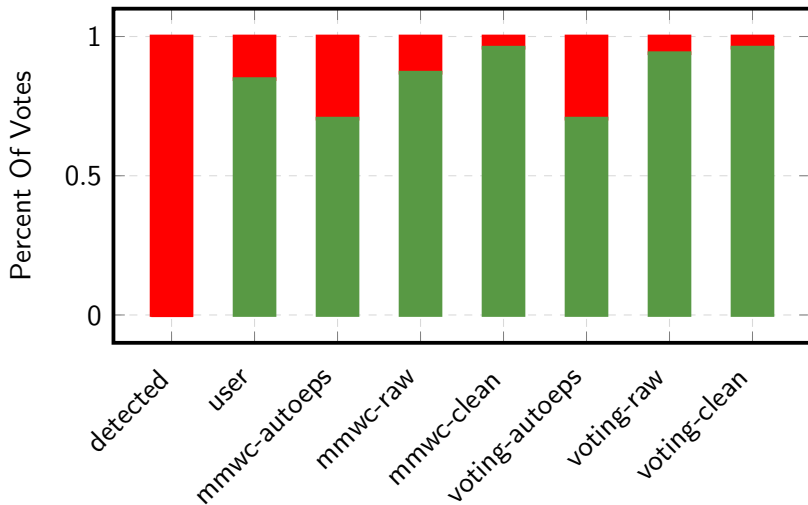
Removal of outliers does not affect Voting much.



Semantical Results

■ Yes ■ No

What happened with the autoeps-variants?



Analysis of the auto-eps Variants

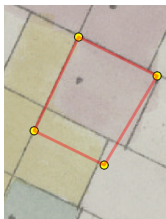
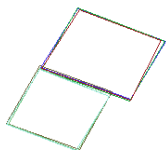
Analysis of the auto-eps Variants

There were 45 groups where both autoeps-variants failed.

Analysis of the auto-eps Variants

There were 45 groups where both autoeps-variants failed.

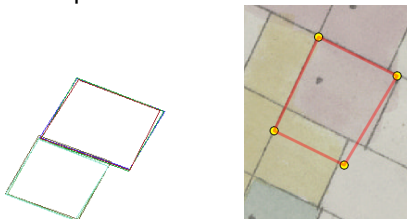
Example:



Analysis of the auto-eps Variants

There were 45 groups where both autoeps-variants failed.

Example:



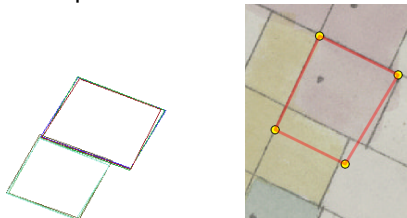
They got confused!

Analysis of the auto-eps Variants

There were 45 groups where both autoeps-variants failed.

There were two groups only the autoeps-variants could solve.

Example:

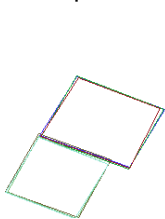


They got confused!

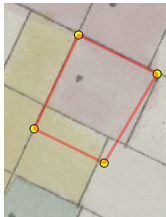
Analysis of the auto-eps Variants

There were 45 groups where both autoeps-variants failed.

Example:

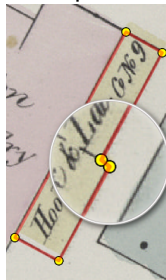


They got confused!



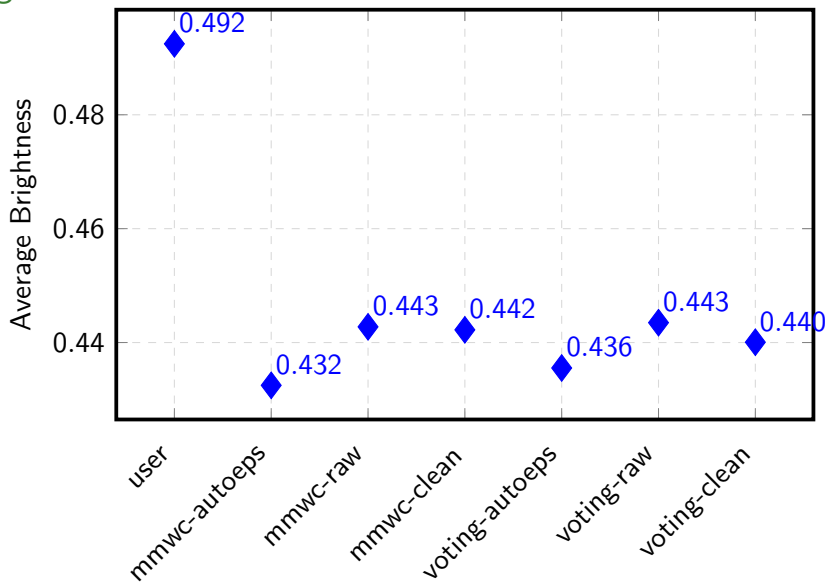
There were two groups only the autoeps-variants could solve.

Example:



Brightness Results

Brightness Results



Conclusion

Conclusion

Algorithmically

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Implications from the Results

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Implications from the Results

The cluster-based algorithms need two pre-processing steps.

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Implications from the Results

The cluster-based algorithms need two pre-processing steps. One of them can be spared without loss of quality.

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Implications from the Results

The cluster-based algorithms need two pre-processing steps. One of them can be spared without loss of quality. This choice can be made with regard to the data.

Conclusion

Algorithmically

We proposed three Algorithms to solve the problem, using pure geometry or cluster-based approaches.

Implications from the Results

The cluster-based algorithms need two pre-processing steps. One of them can be spared without loss of quality. This choice can be made with regard to the data.

The Voting Algorithm performs better than the MWWC Algorithm.