DISTRIBUTED RANDOM FOREST CLASSIFICATION OF URBAN MOBILE MAPPING DATA

Christian Alis
University College London, UK

IQmulus, Final Workshop

Bergen, September 21, 2016

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Distributed Random Forest classification of urban mobile mapping data

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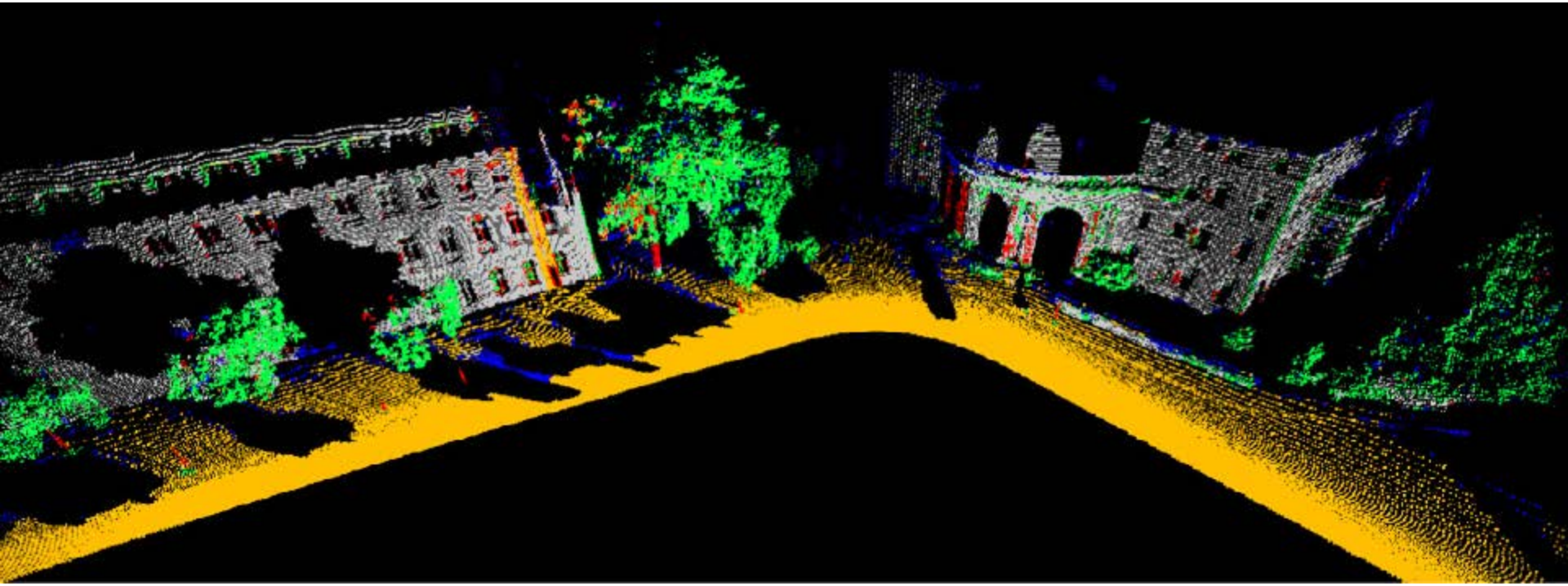

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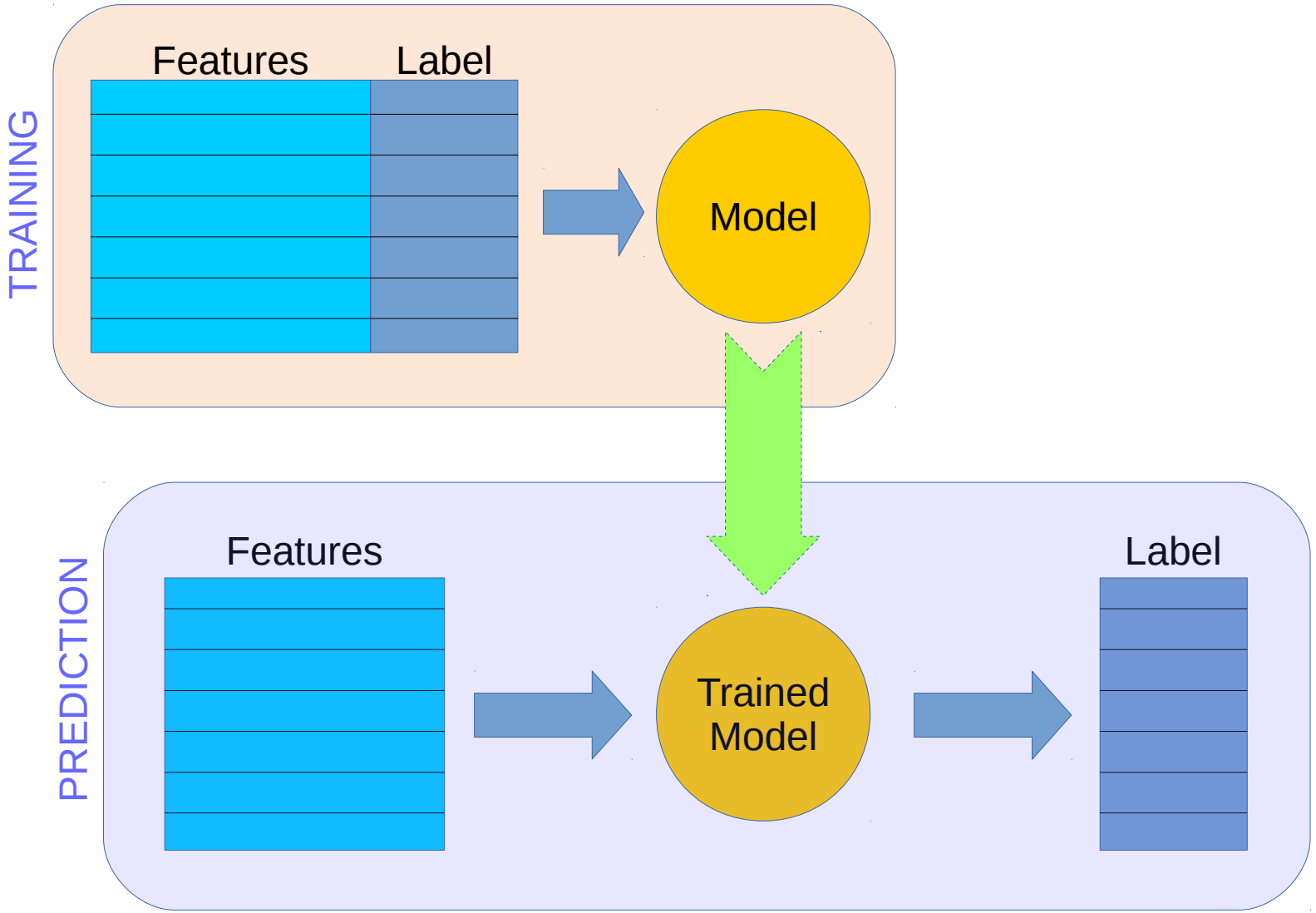

TRAINING
Features
Label
Model
PREDICTION
Features
Trained
Model
Label

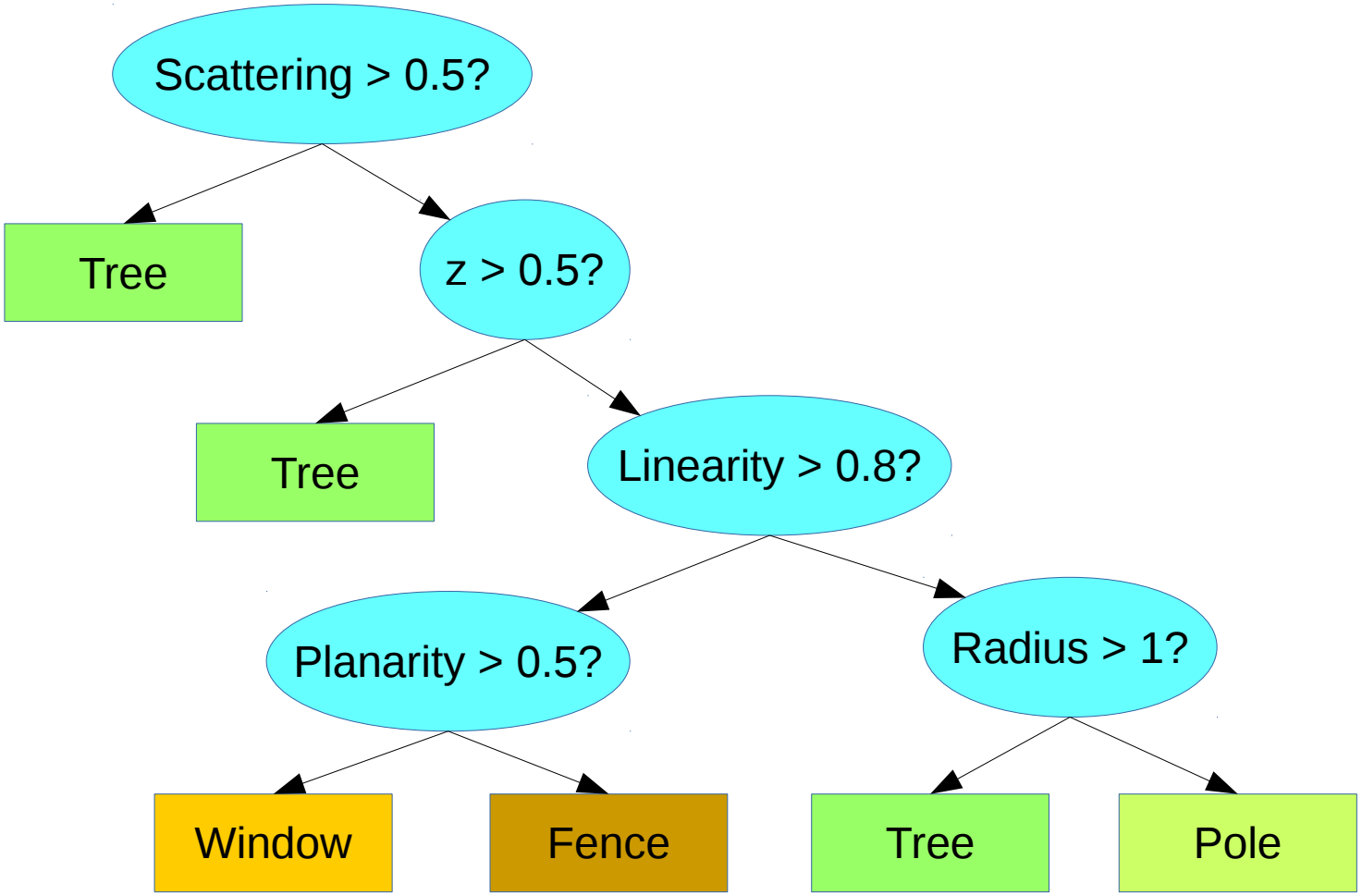
Point cloud classification features

- Linearity
- Planarity
- Scattering
- Omnivariance
- Anisotropy
- Eigenentropy
- Eigenvalue sum
- Change of curvature
- Z value

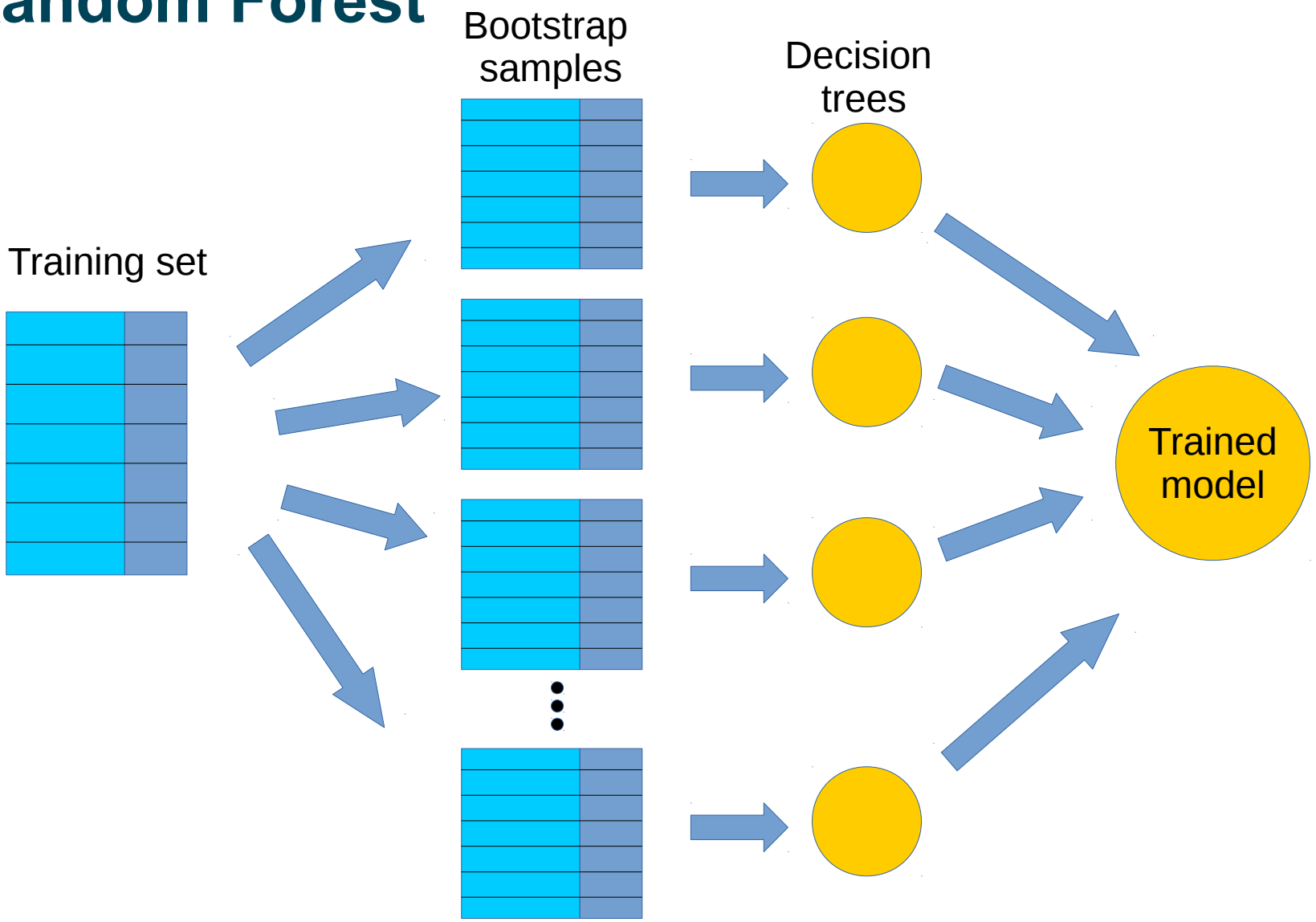
- Radius
- Density
- Verticality
- Z range
- Z standard deviation
- 2D radius
- 2D density
- 2D eigenvalue sum
- 2D eigenvalue ratio

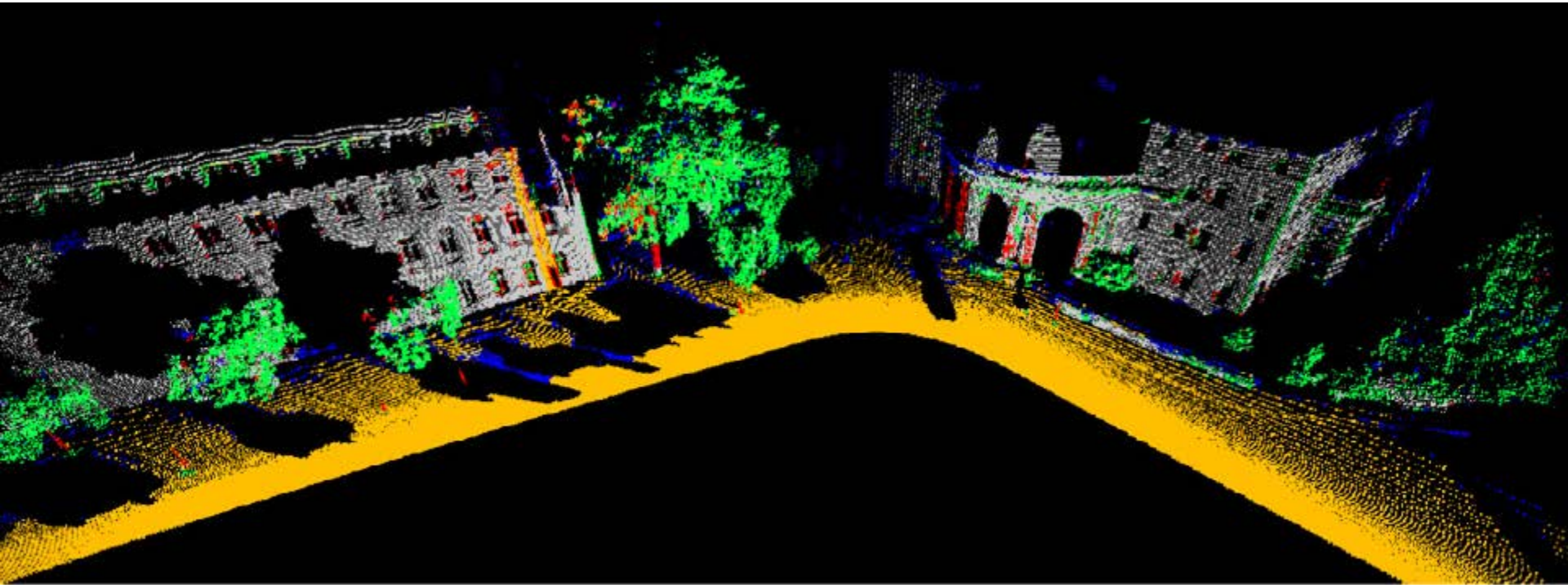
Features are computed based on neighbourhood of the point

Decision Tree



Random Forest





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https://commons.wikimedia.org/wiki/File:BigData_2267x1146_white.png

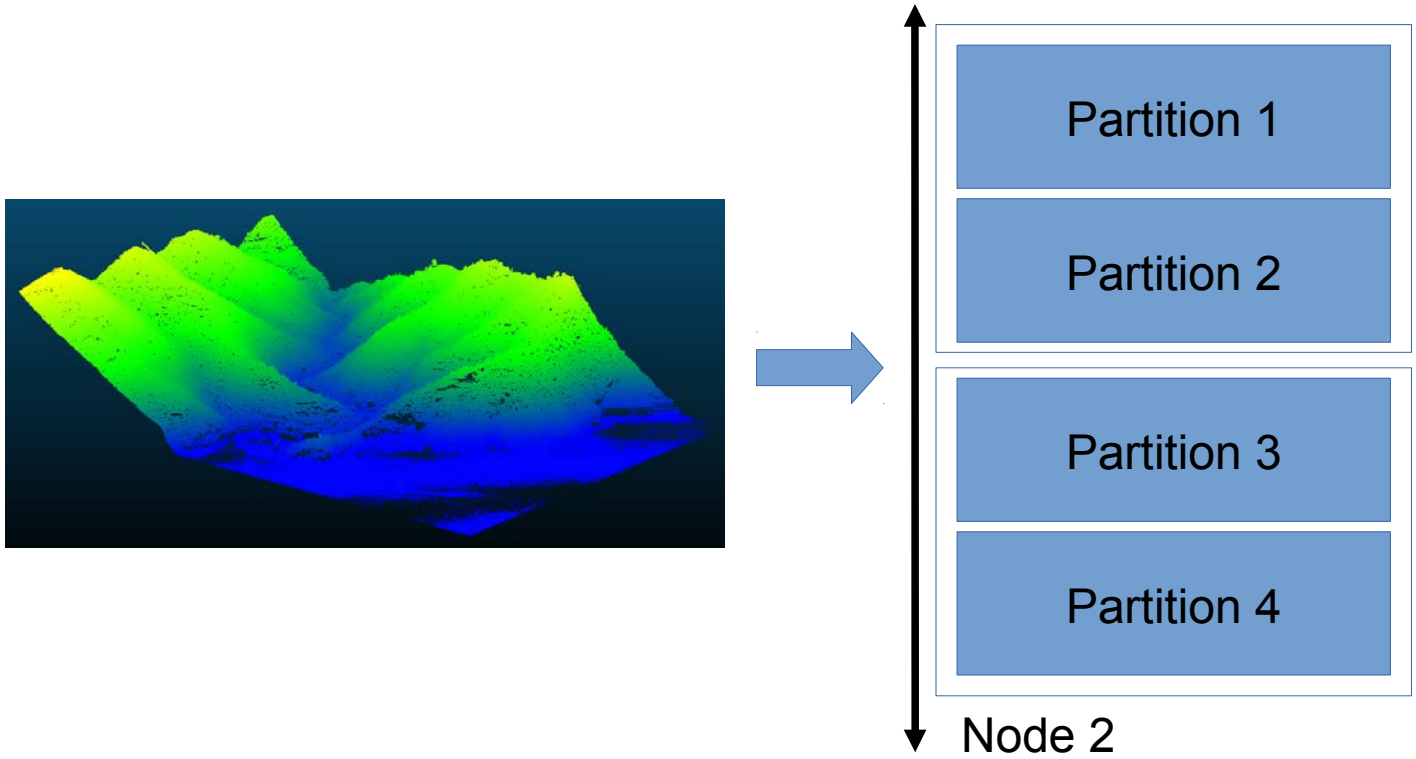
Apache Spark

- A processing engine for distributed computation
- Able to scale from single to multiple machines
- Allows coding using different languages
- Very active development and user community
- Allows processing of non-spatial data
- Has a machine learning library with random forest

- No built-in support for point clouds
- Partitioning

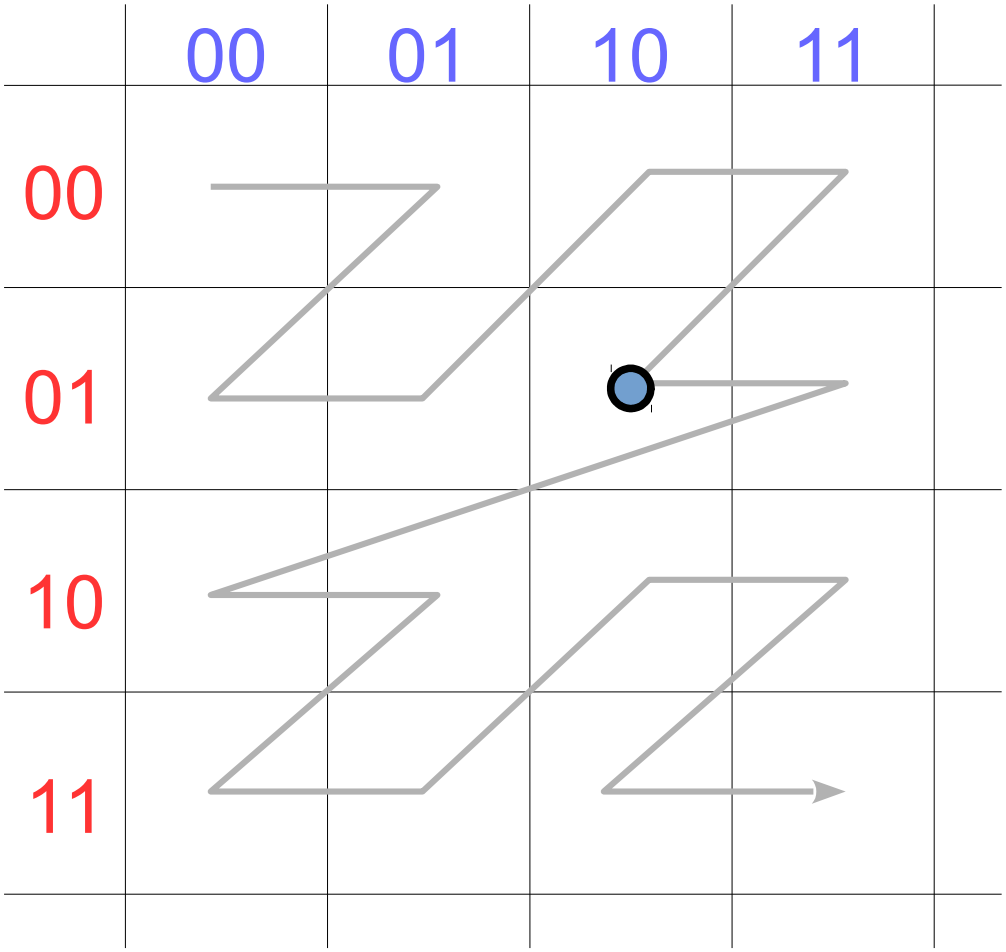
The challenge of data partitioning

- Not all data would fit on a single machine
- Network I/O is too slow to transfer data as needed



Z-order indexing

A space-filling curve with adjustable level of detail



1 0
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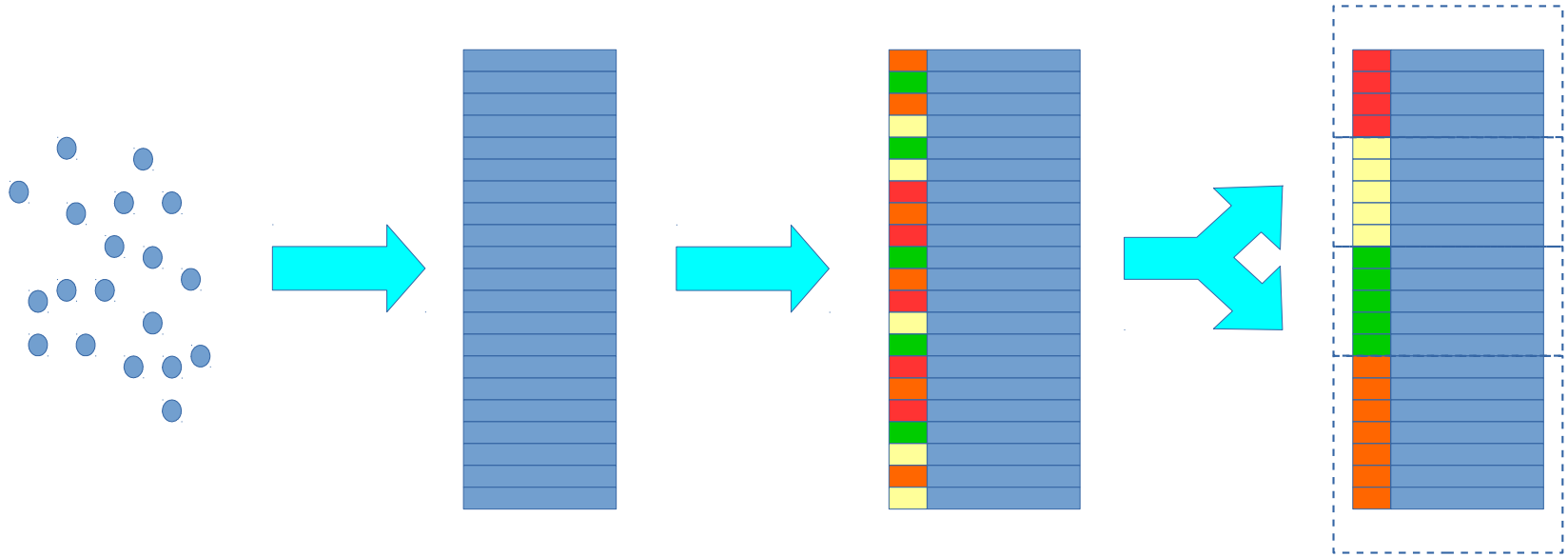
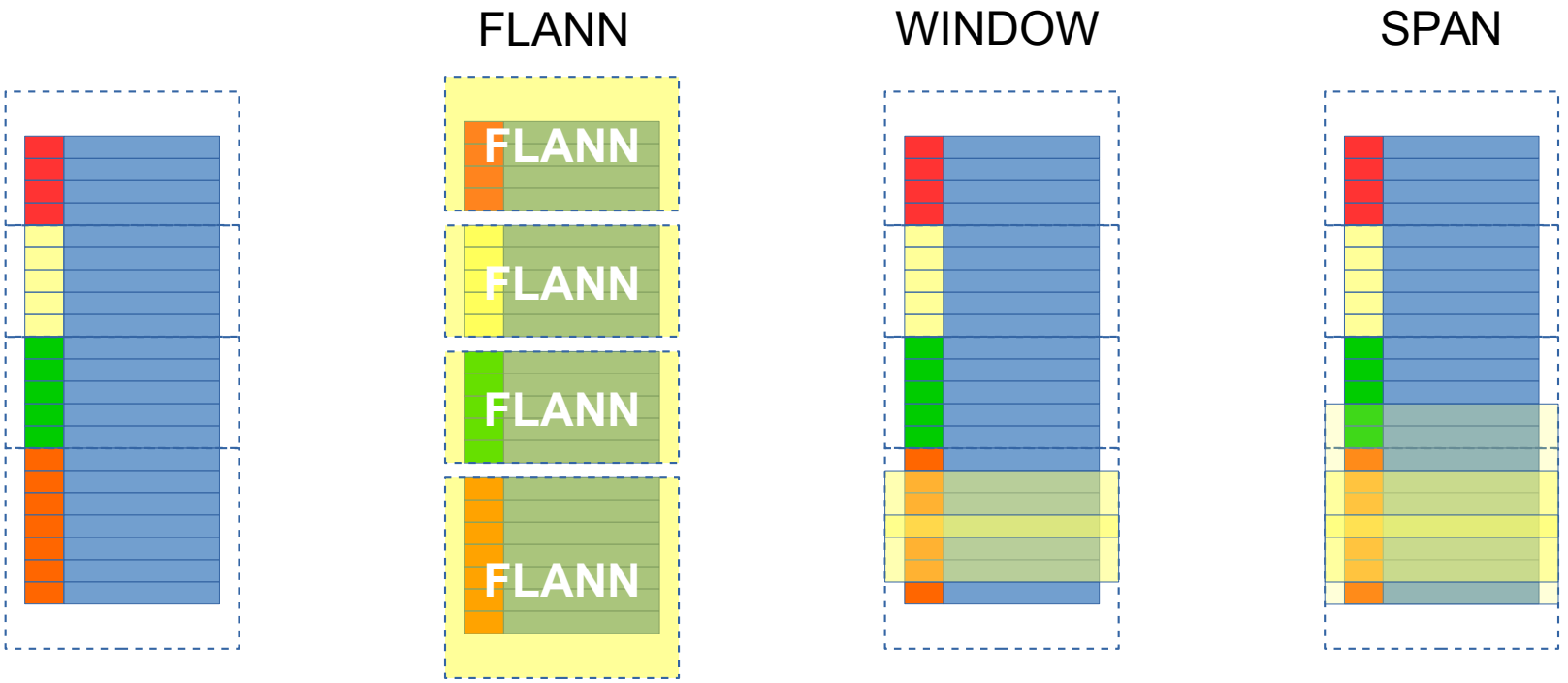
Partitioning point clouds using z-order

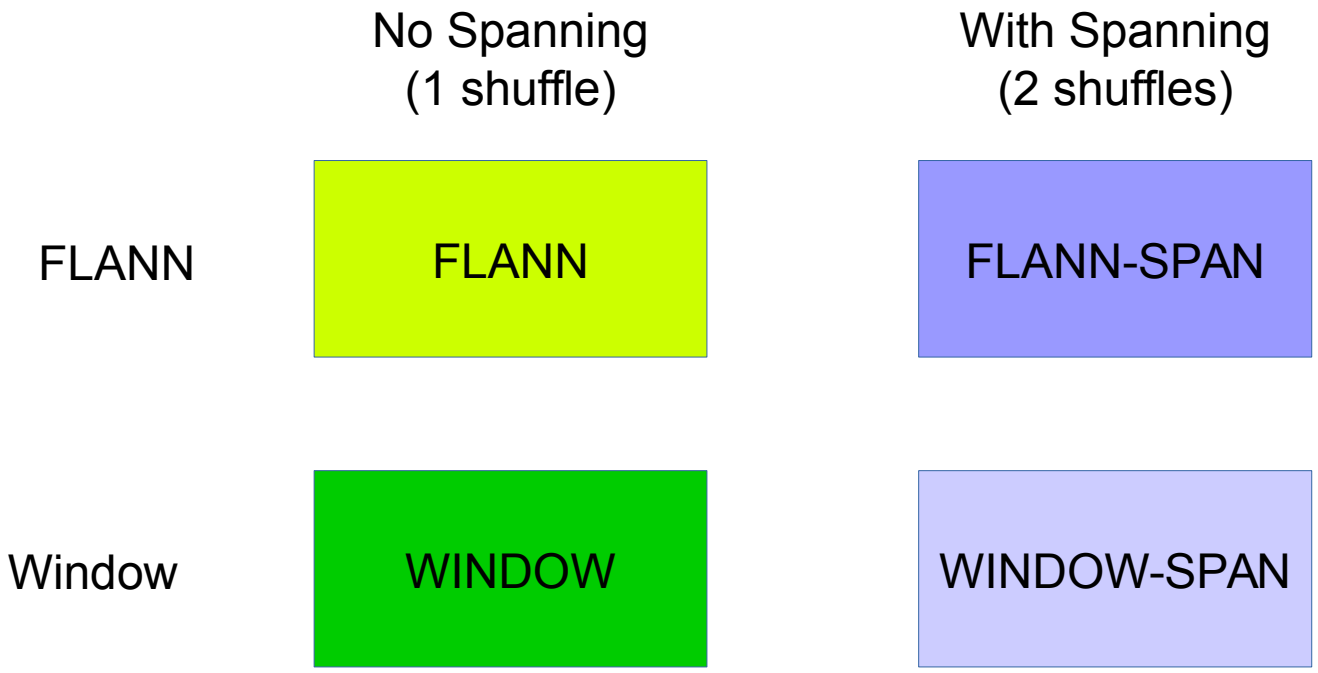


Point cloud | Table of points | Indexed table | Partitioned point cloud

Ways of doing kNN + feature extraction



Workflows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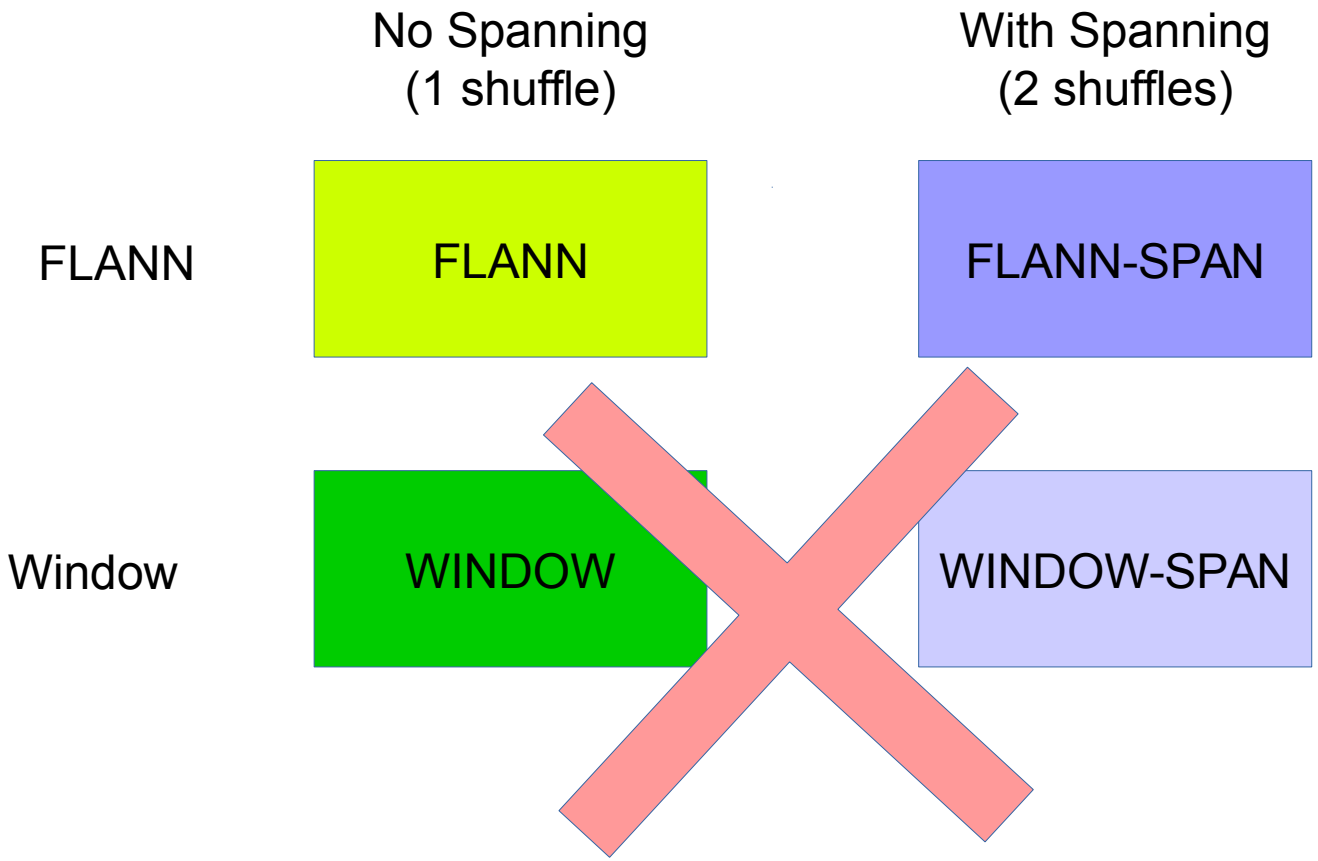
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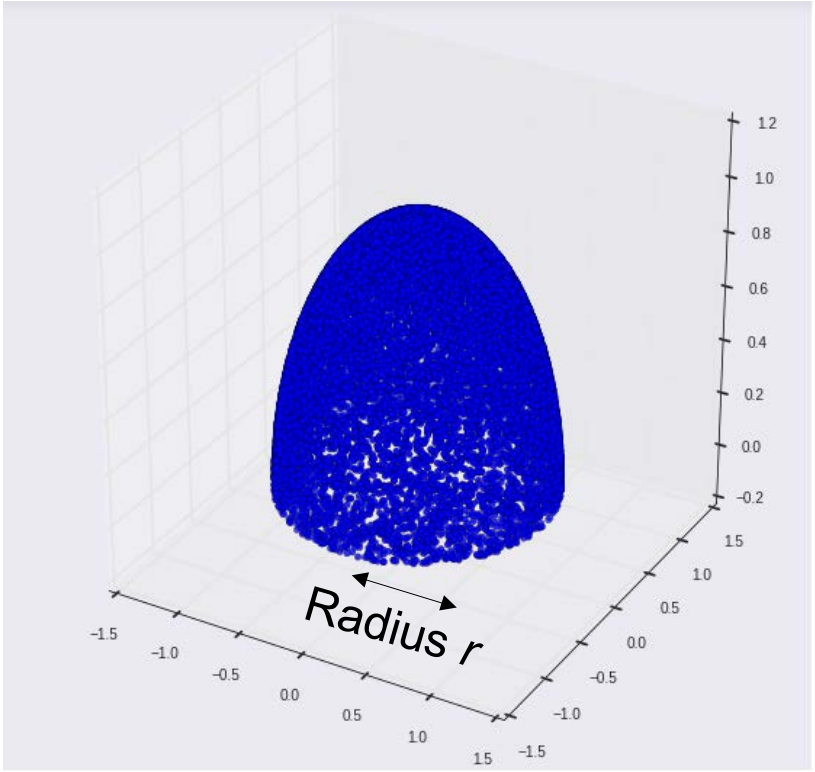
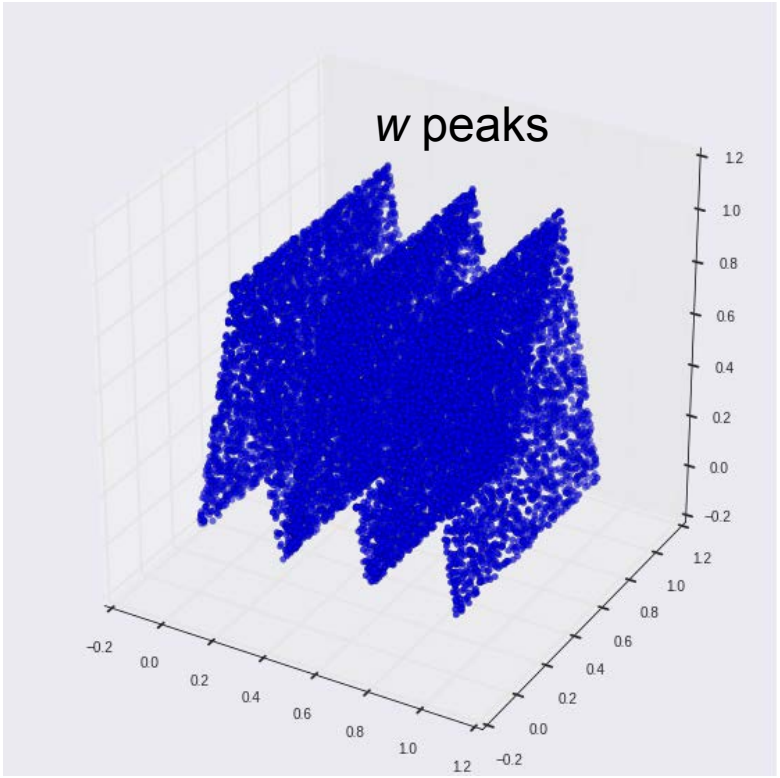
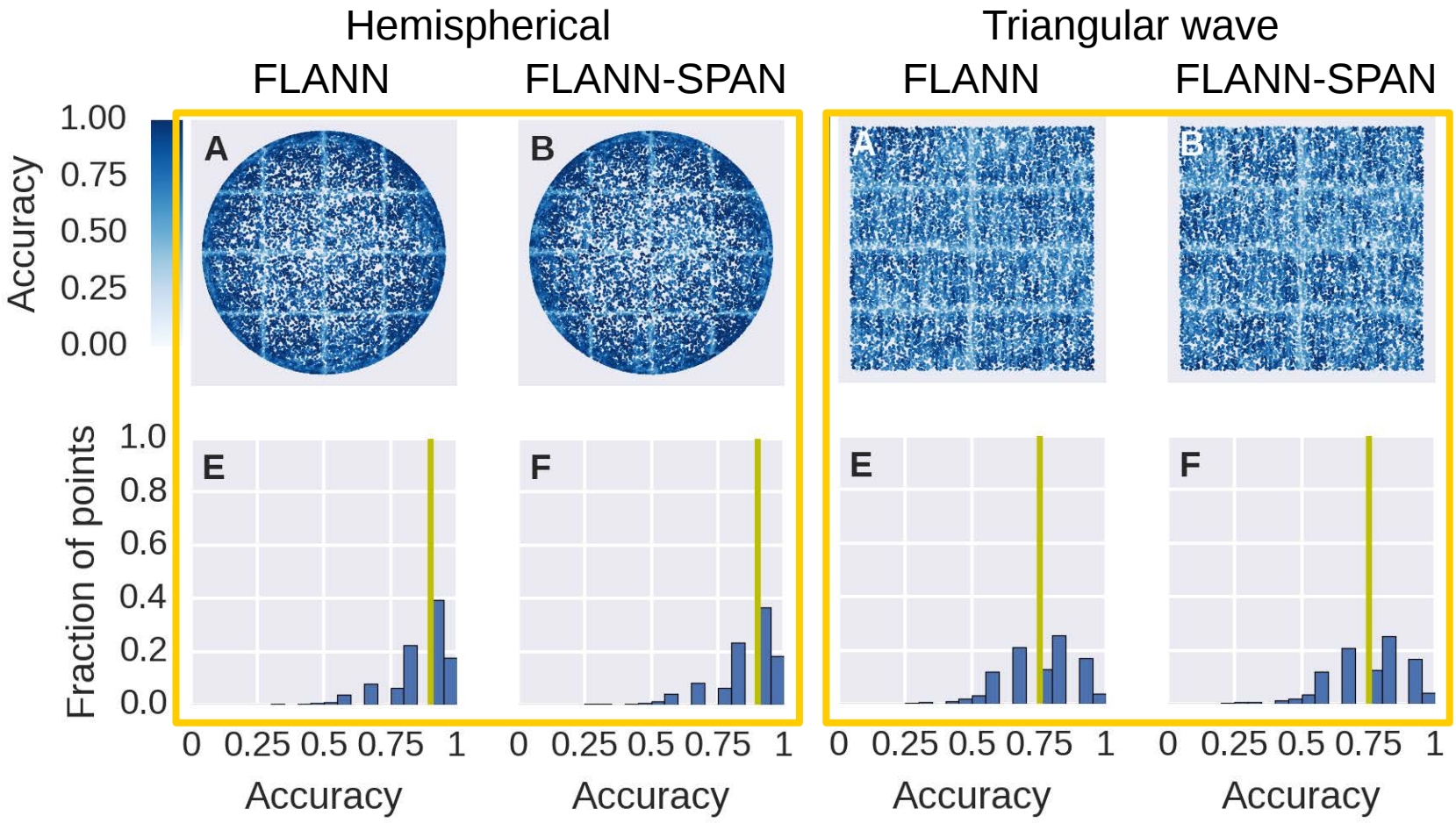


Triangular wave



Accuracy at different points

Results with or without spanning are similar



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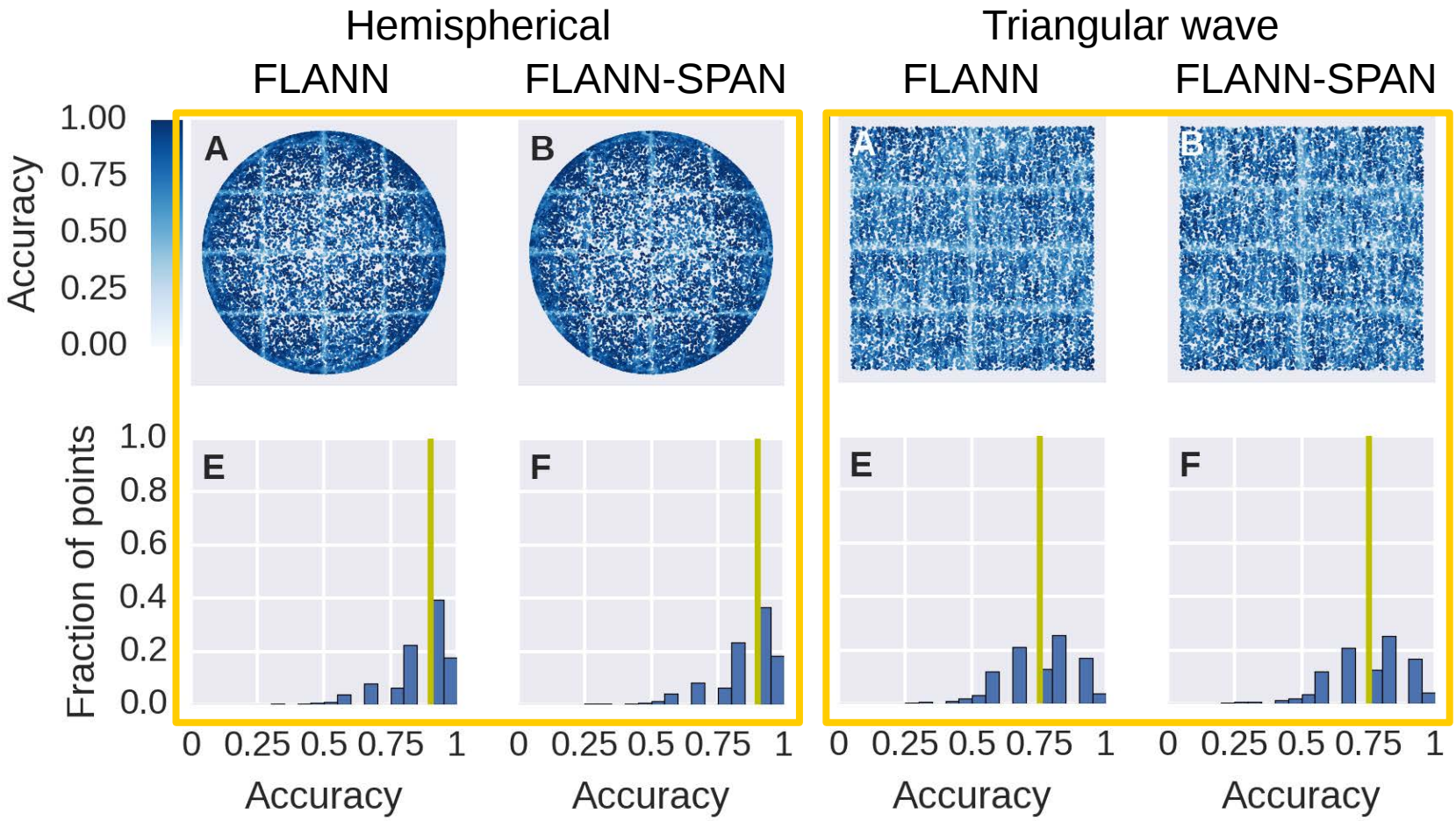

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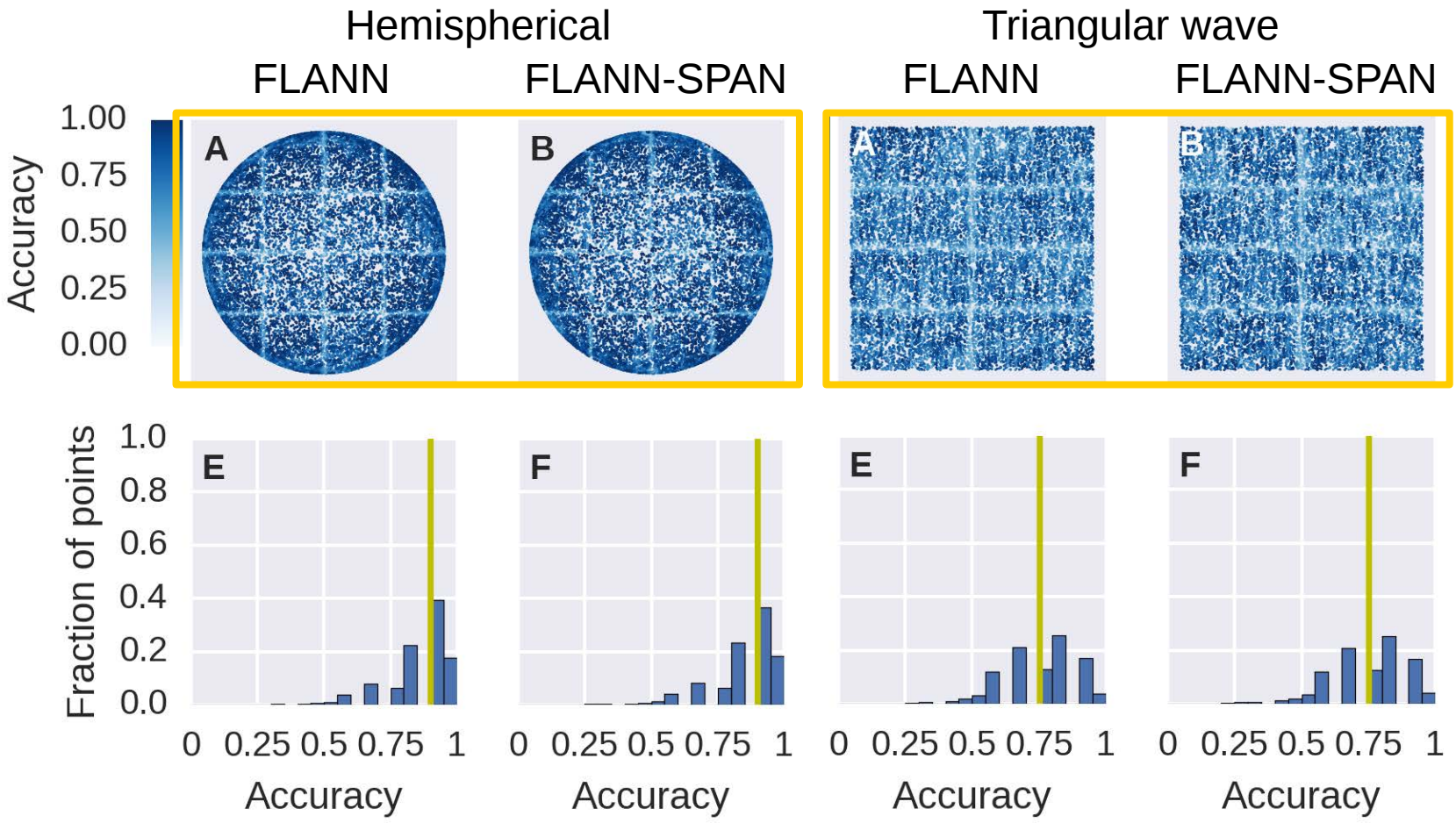
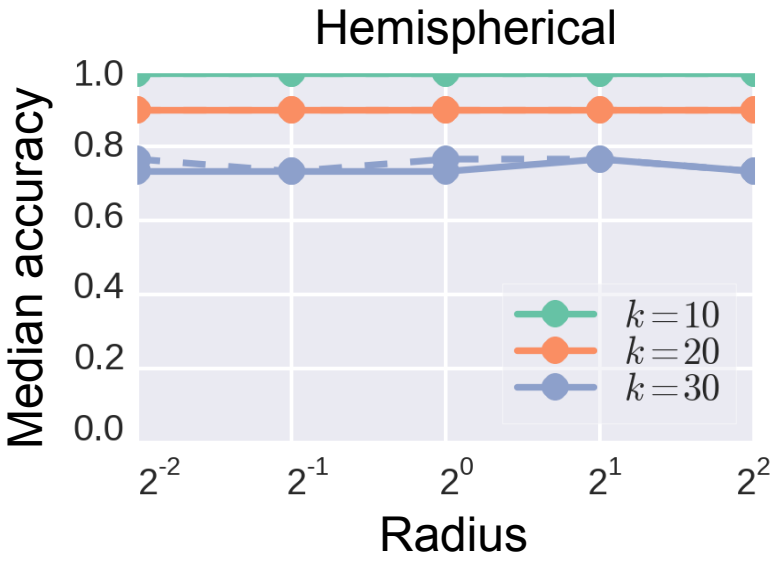
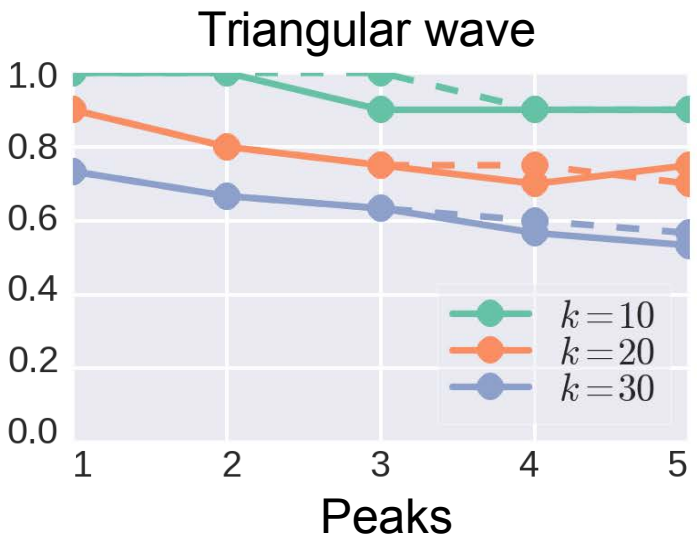


Accuracy for different neighbourhood sizes

Accuracy gets worse with increasing *k*





Spark MLlib machine learning library

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- Supports DT, random forest and GBTree
- Interface similar to scikit-learn
- RDD and DataFrame-based interfaces

Tree/non-tree classification

- Training set
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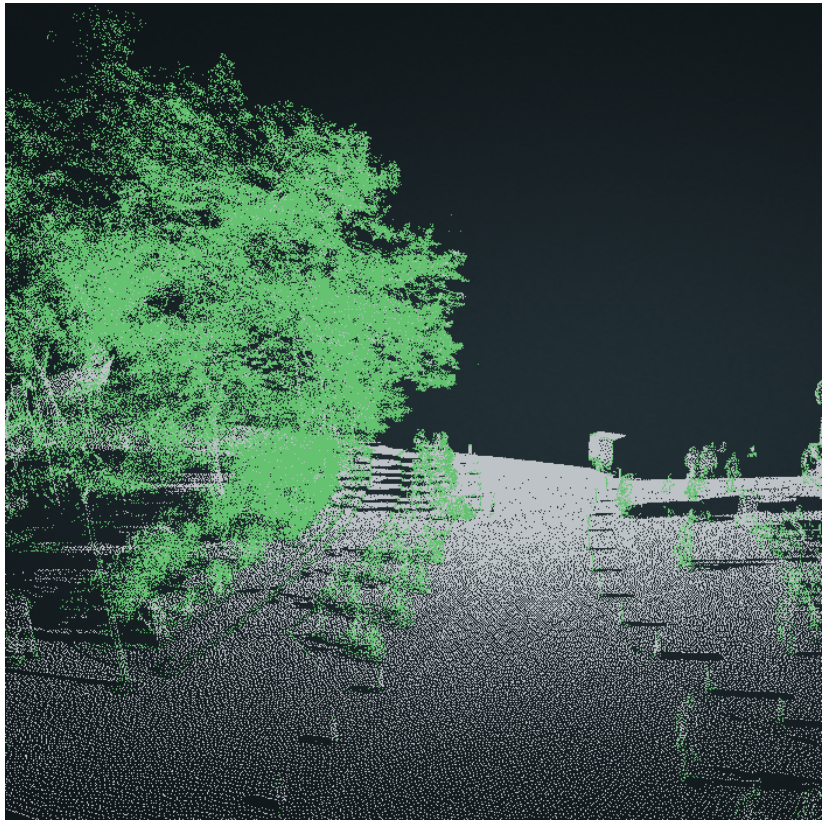

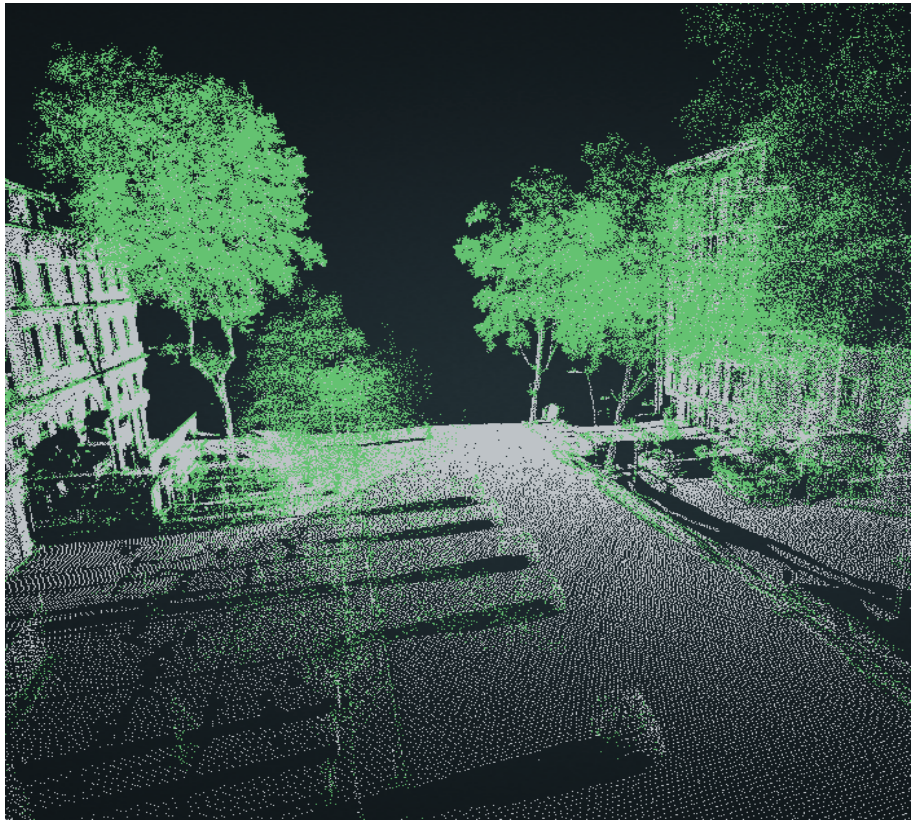

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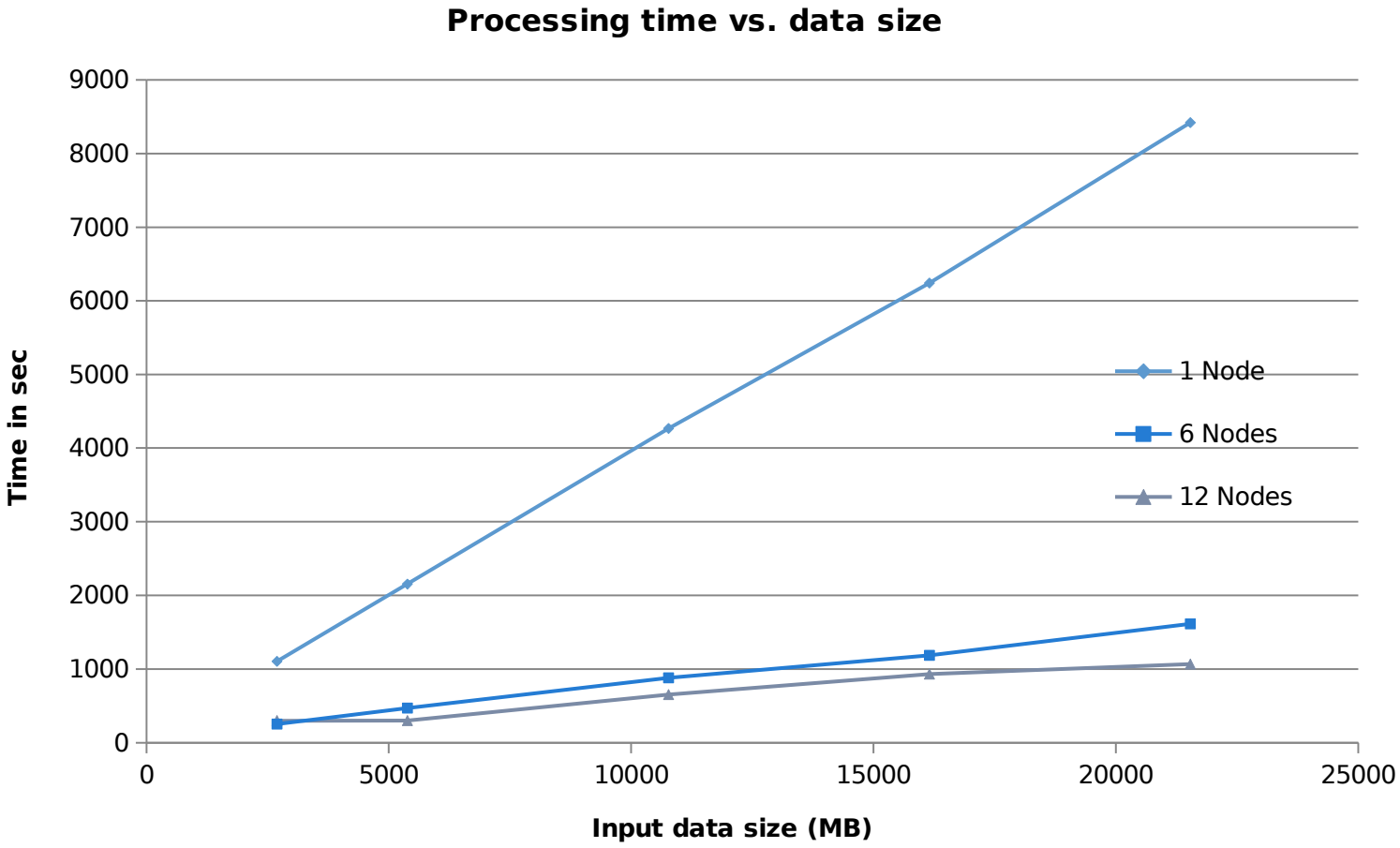
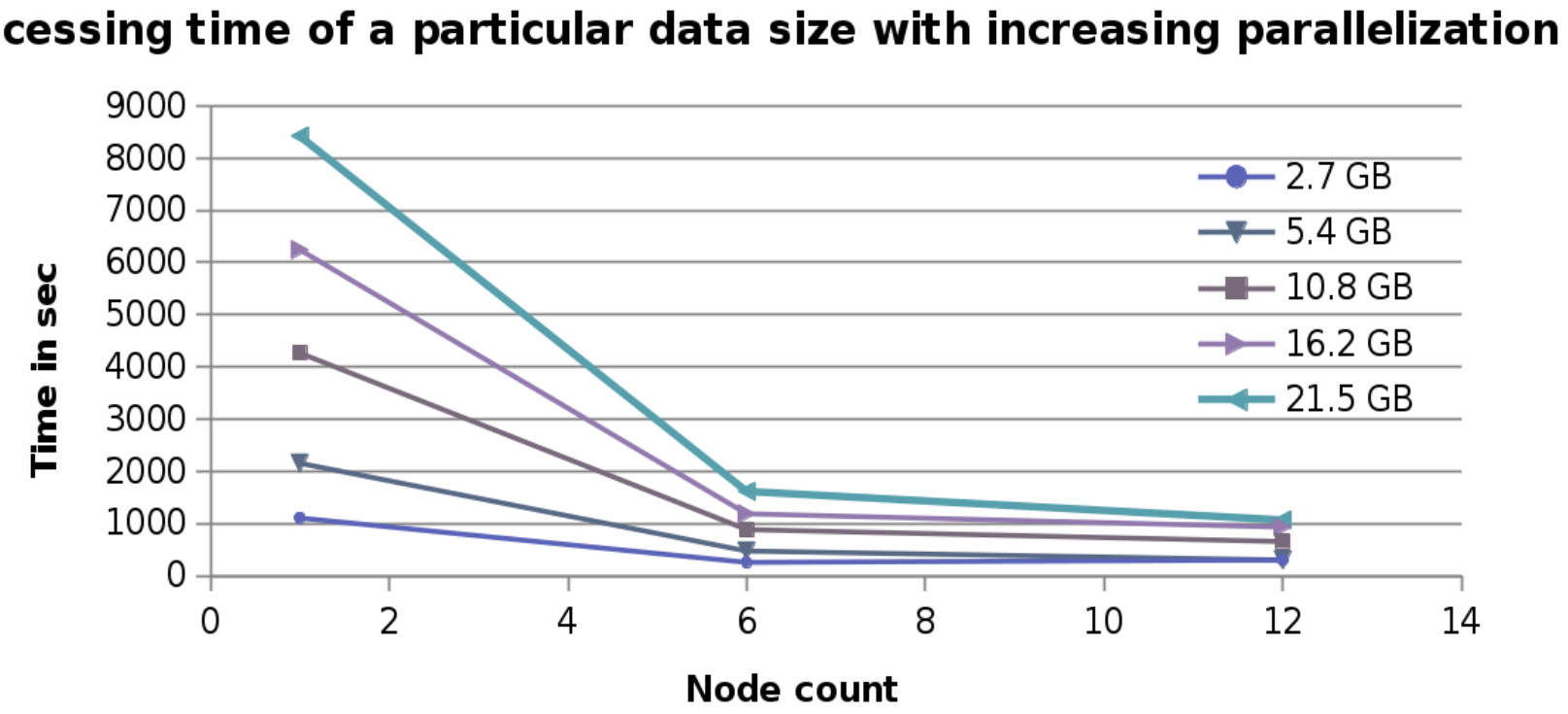


Better scalability for larger data size



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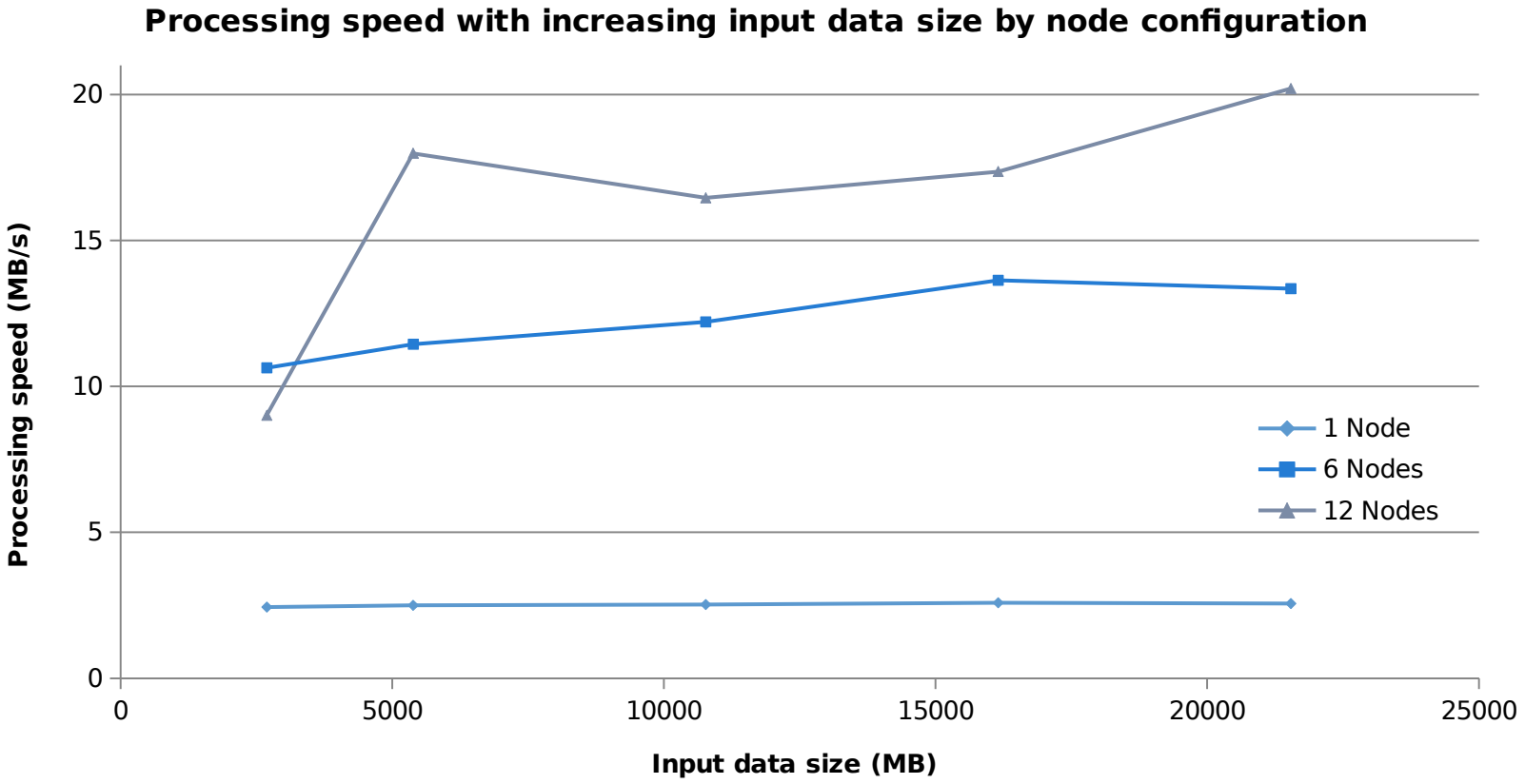

Summary

- Random forests can be used to classify point clouds
- Distributed processing can be performed with Spark
- Z-order partitioning mitigates boundary error
- Spark MLlib allows scalable RF classification

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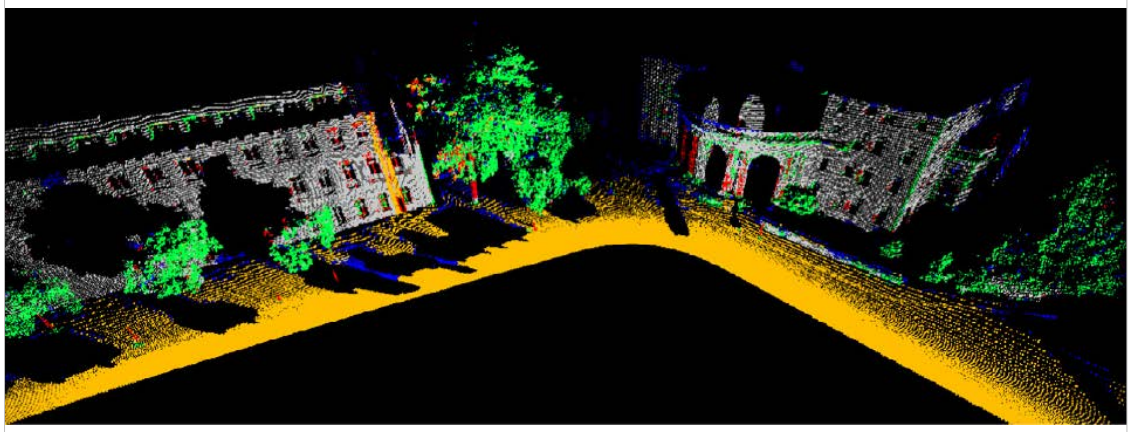

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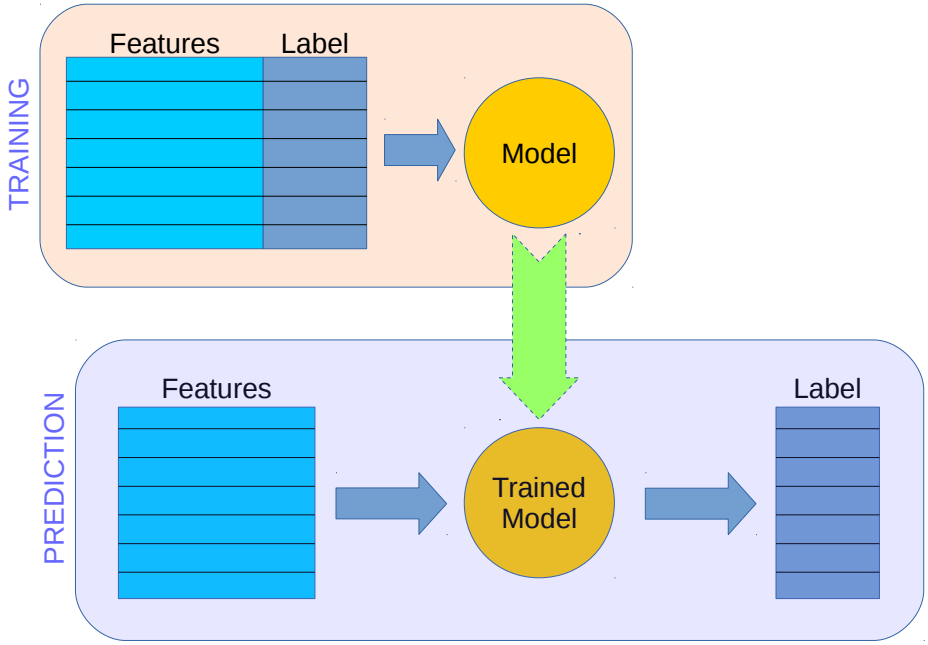
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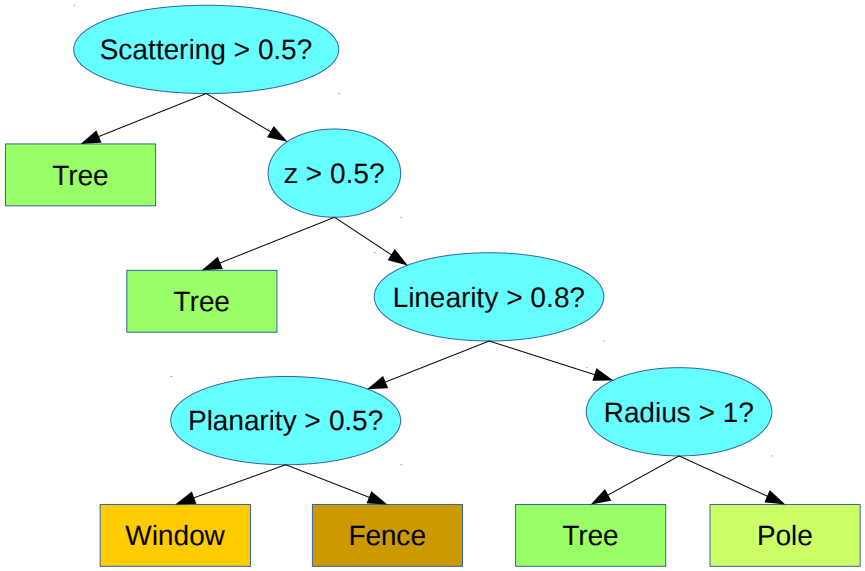
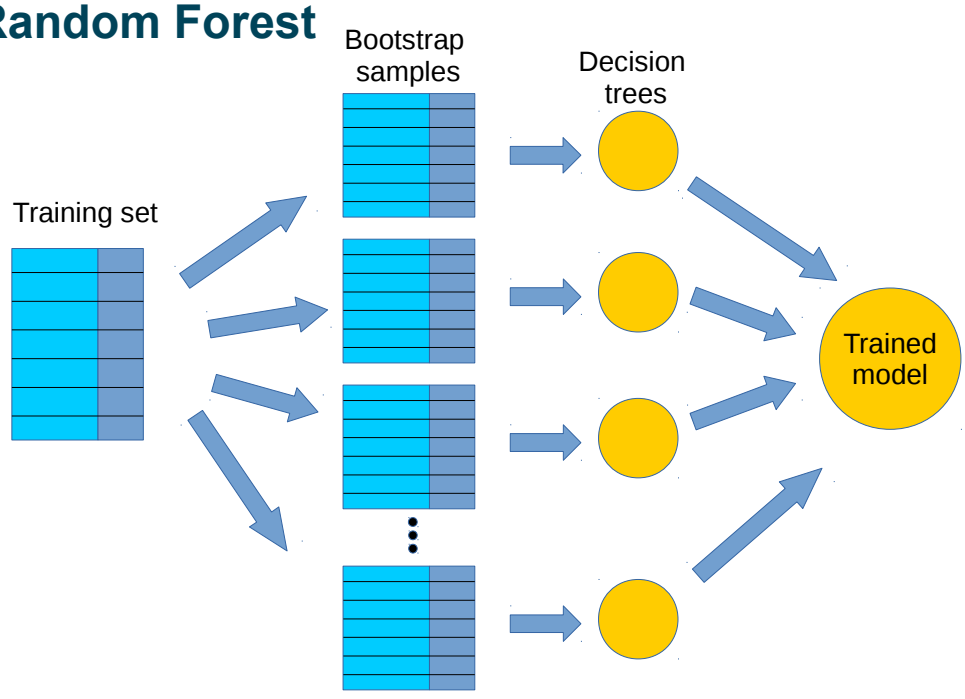
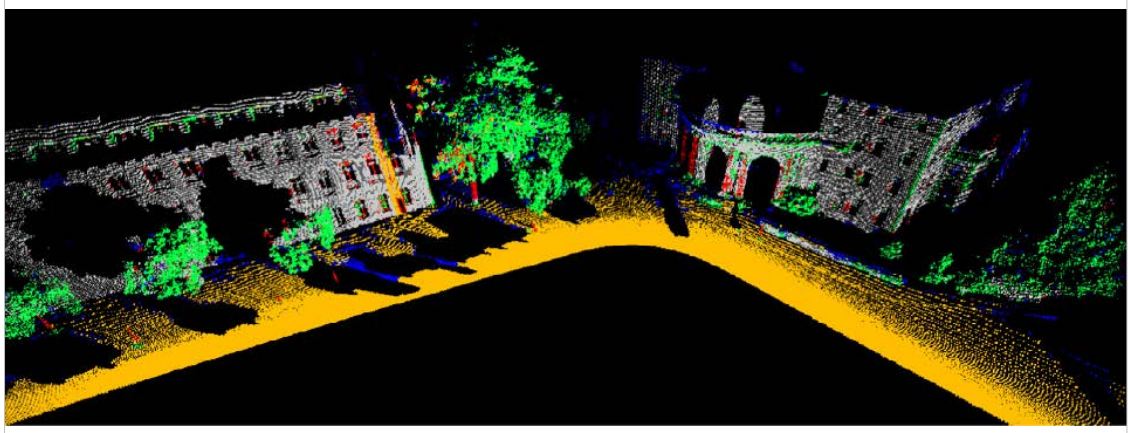


Random Forest





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GeoTrellis, SpatialSpark and Magellan provide support for raster and vector data

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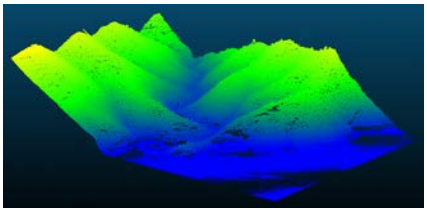

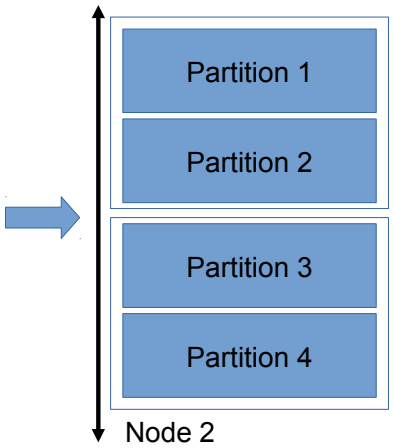

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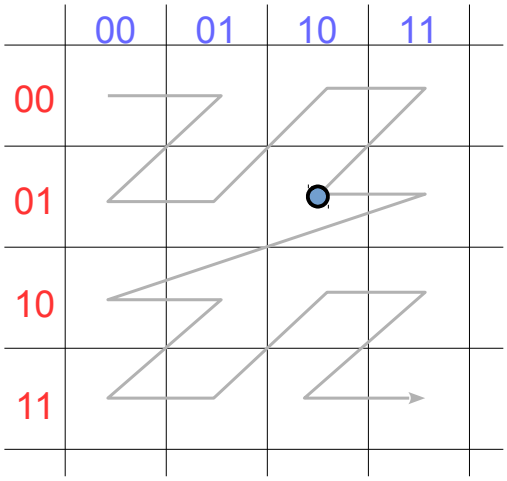

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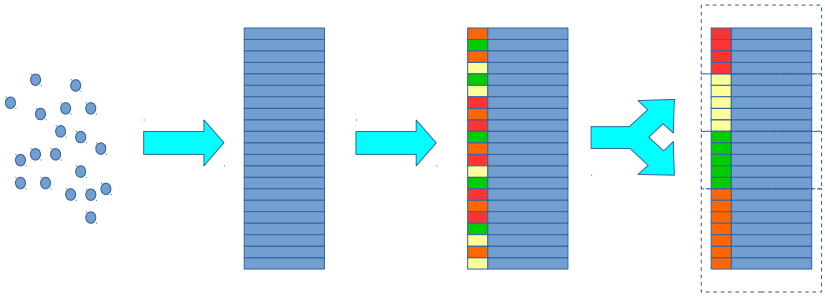

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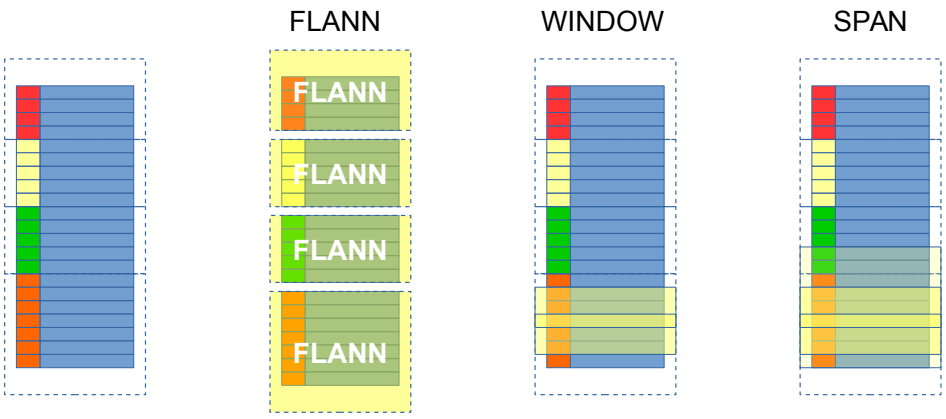
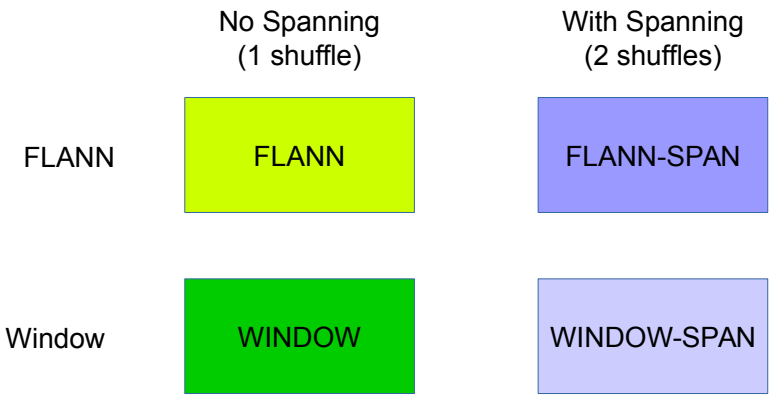


Workflows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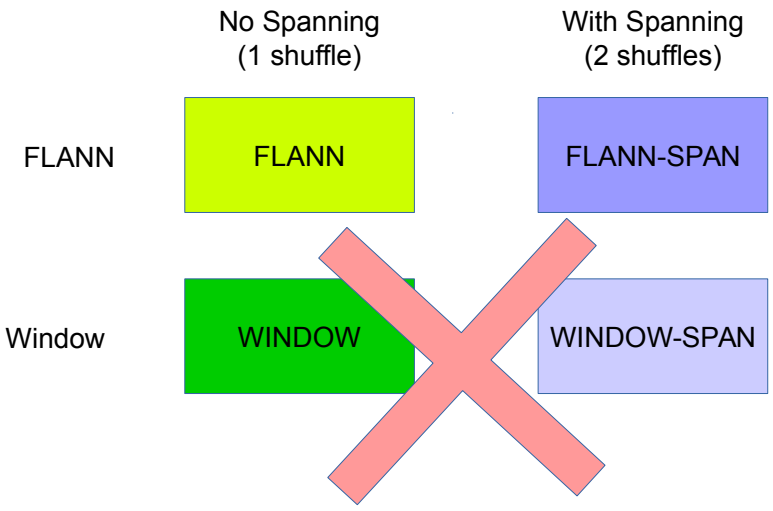
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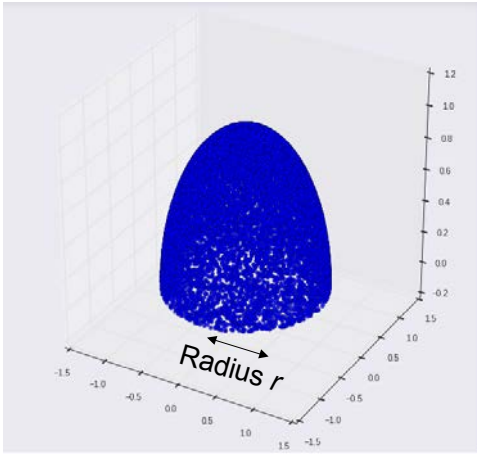

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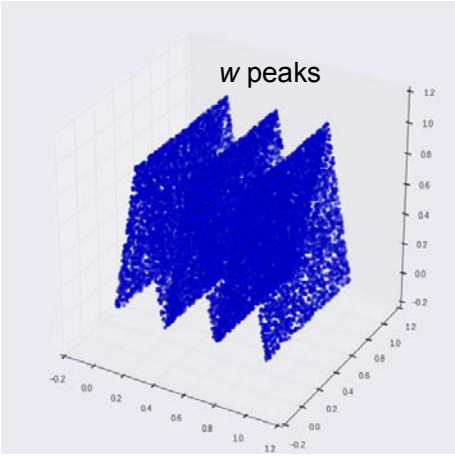

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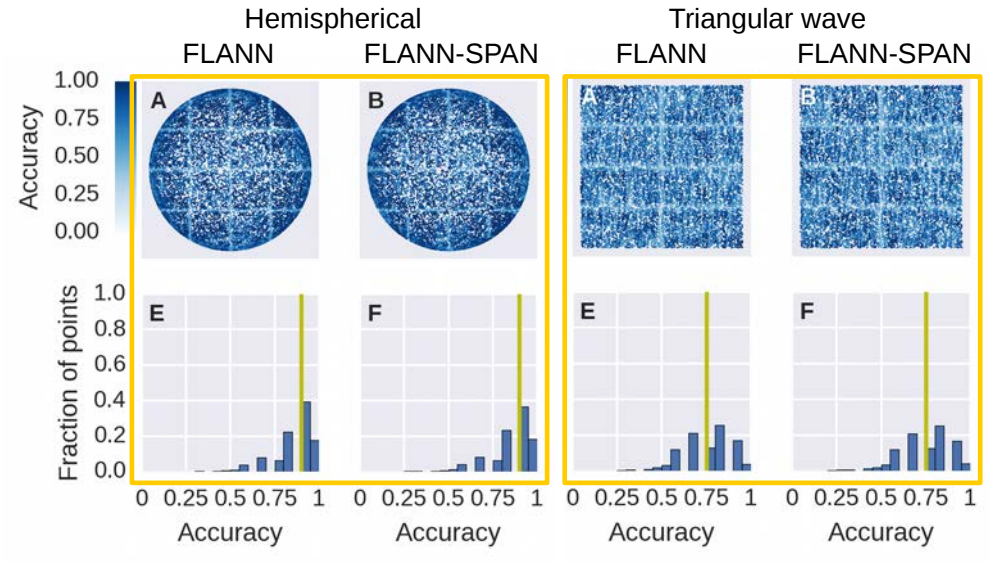

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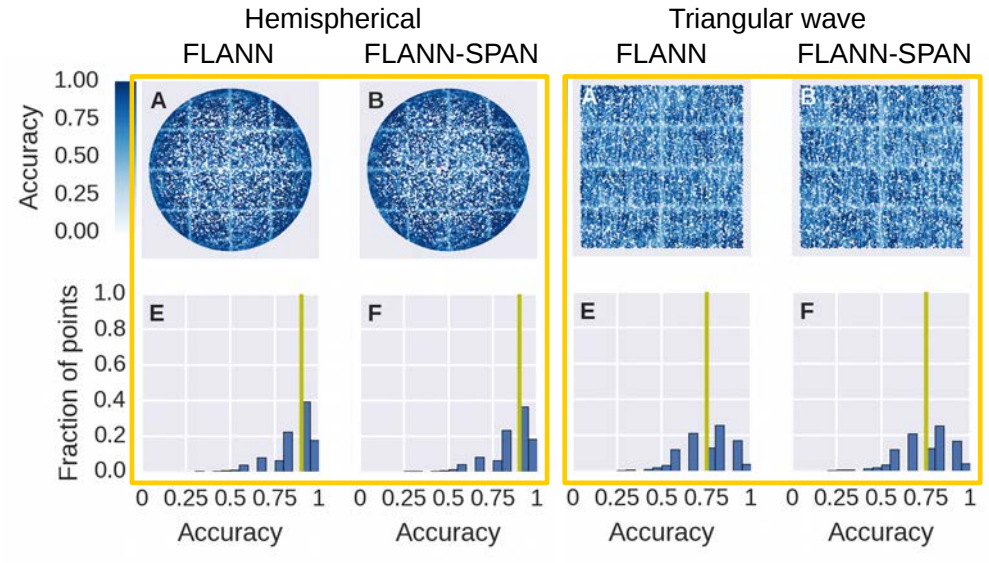

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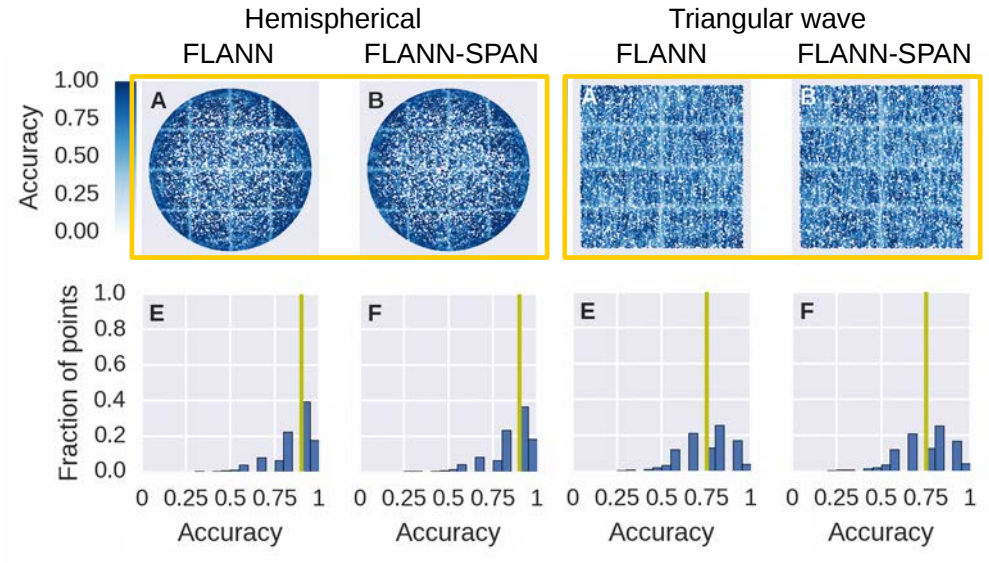

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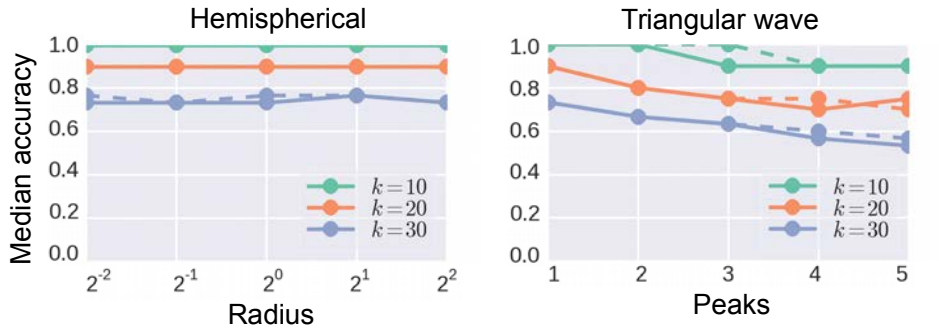

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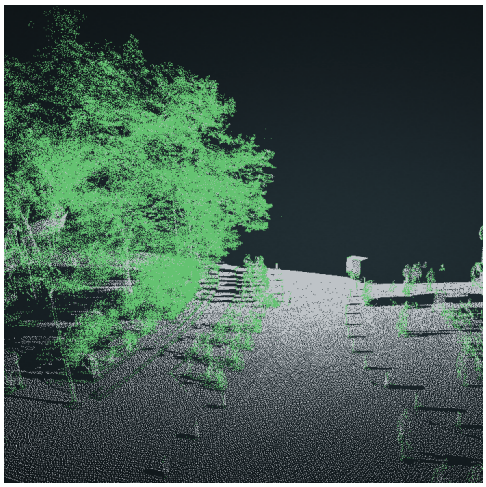

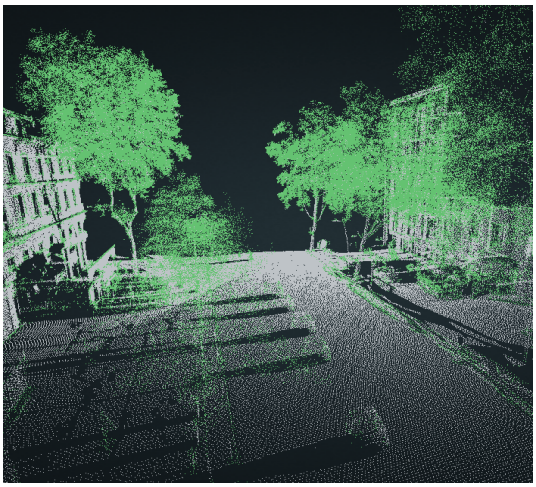

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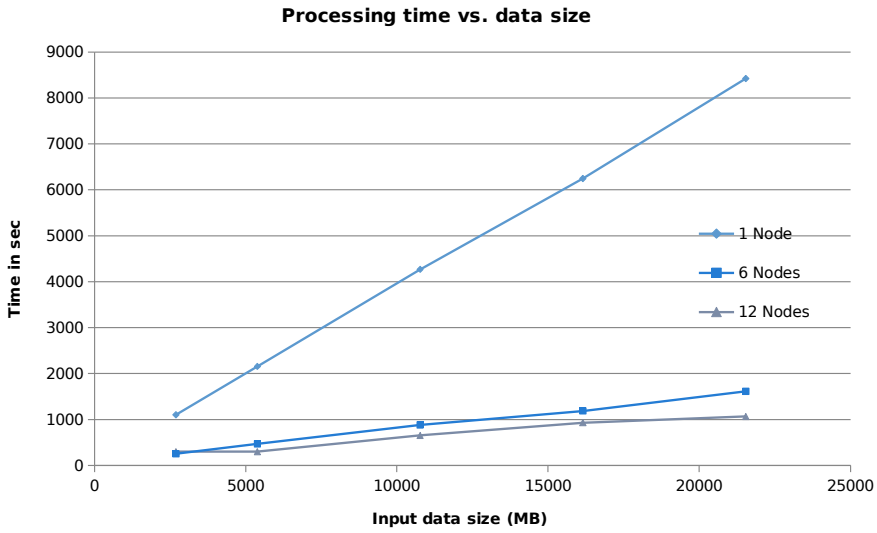

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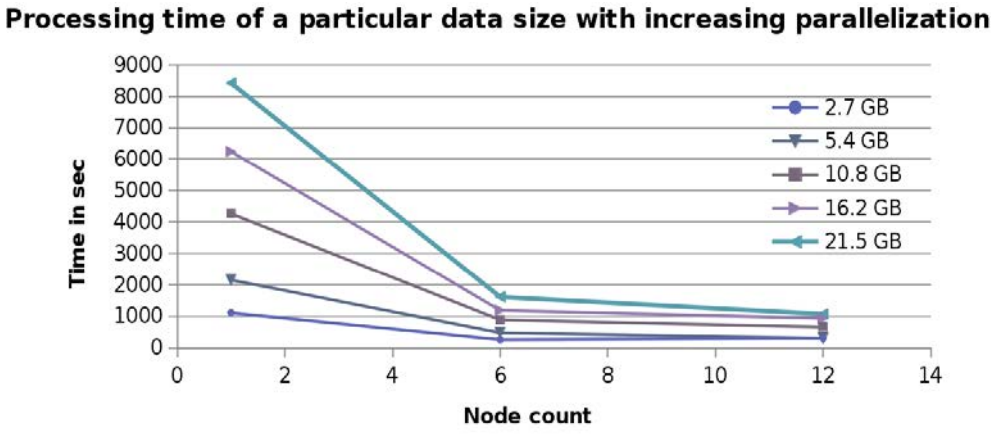

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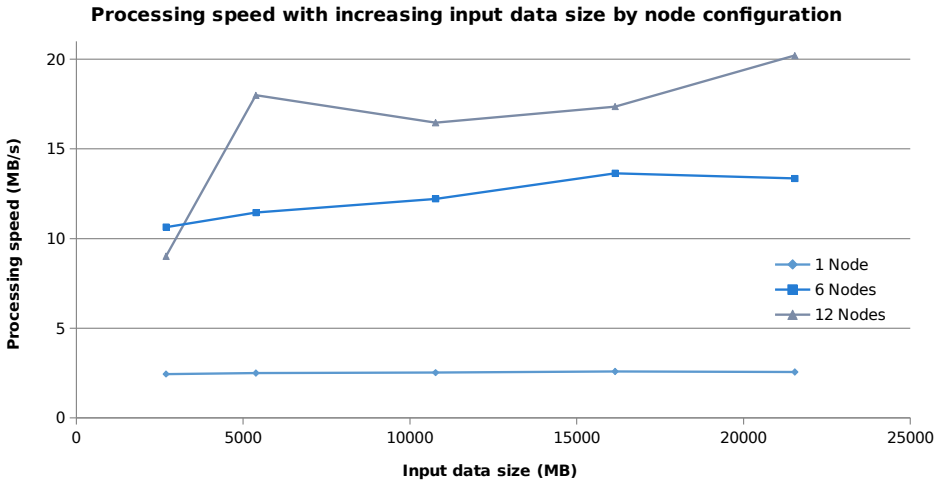

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