Tractography with Machine Learning

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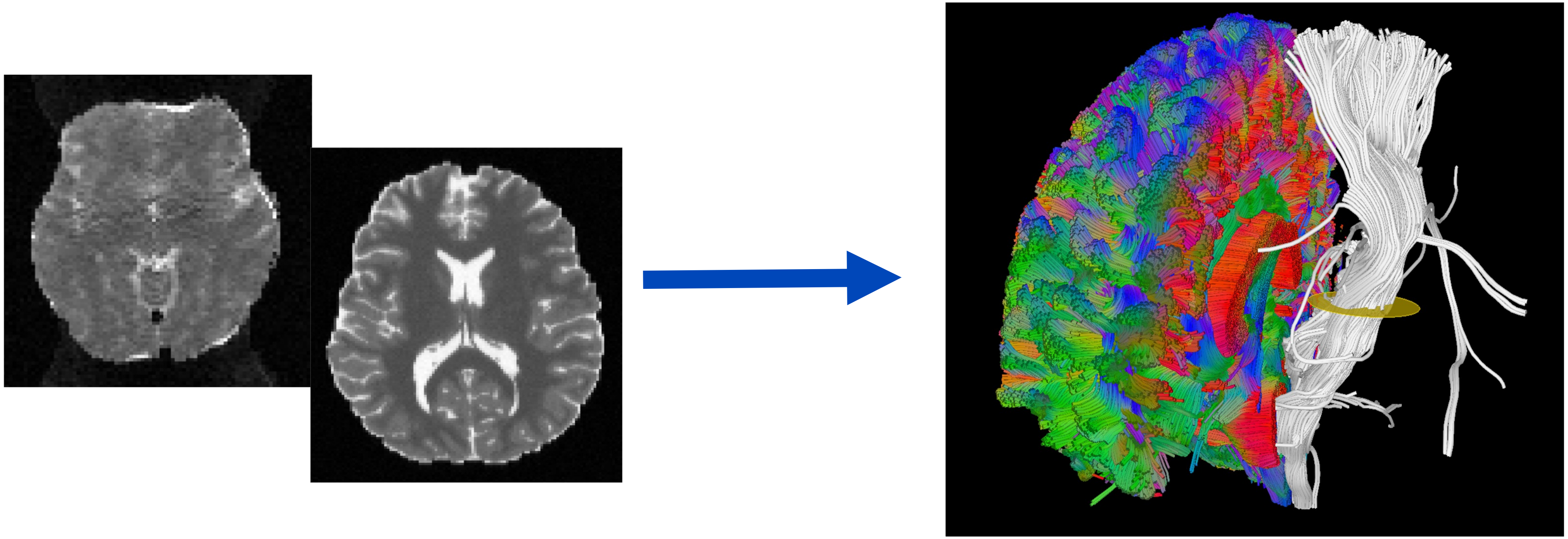
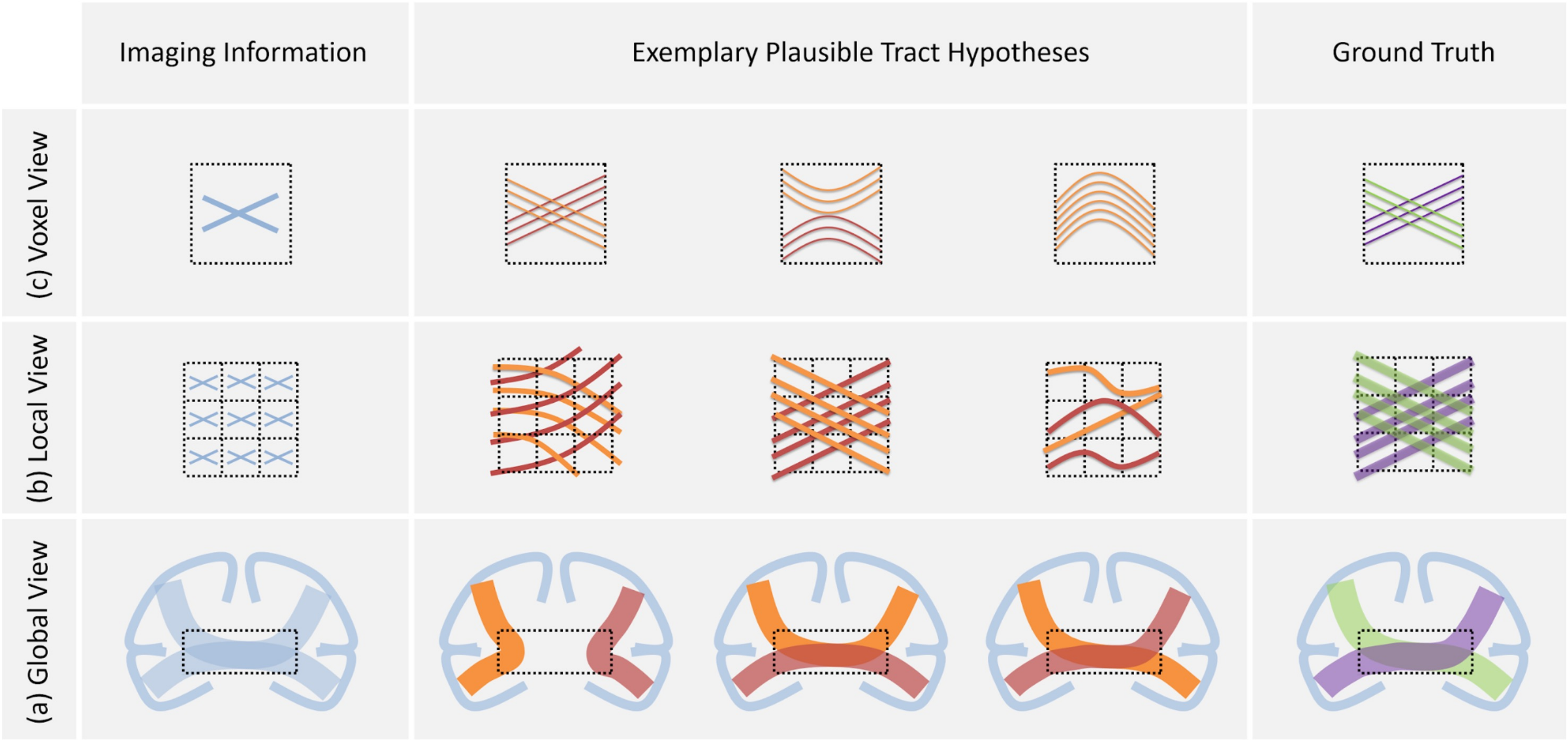
Fiber Tractography



Tractography is a difficult ill-posed problem



Maier-Hein et al., “The Challenge of Mapping the Human Connectome Based on Diffusion Tractography.”, Nature Communications 2017

Can ML help?

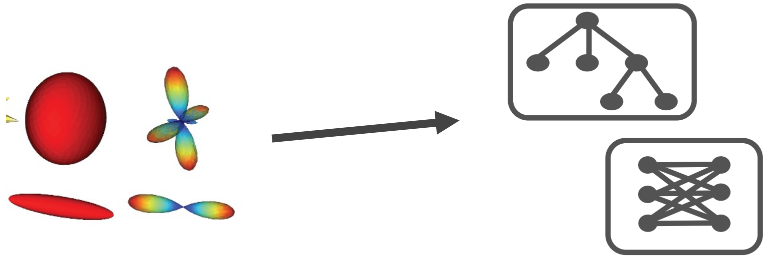
1. No hand-crafted modelling assumptions are necessary.
2. Straight-forward integration of additional sources of information.
3. Possibly reduce manual tinkering with typical tractography parameters.
4. Can include an arbitrarily large neighborhood in their decision making process.

Challenges

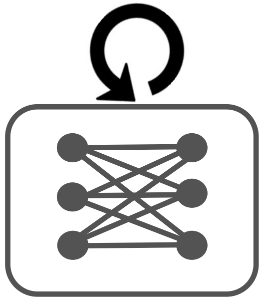
1. Availability and validity of annotated data
2. Problem of generalizability
3. Explainability of decisions made by the ML system

Classes of ML-based tractography approaches

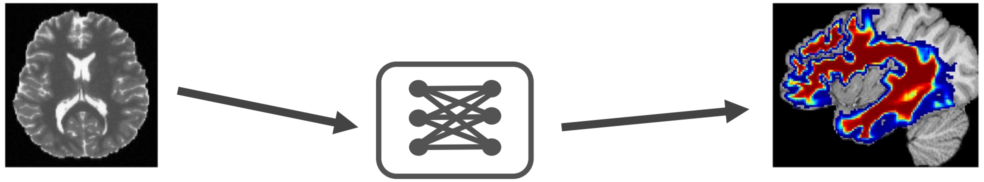
1. ML-based local modeling



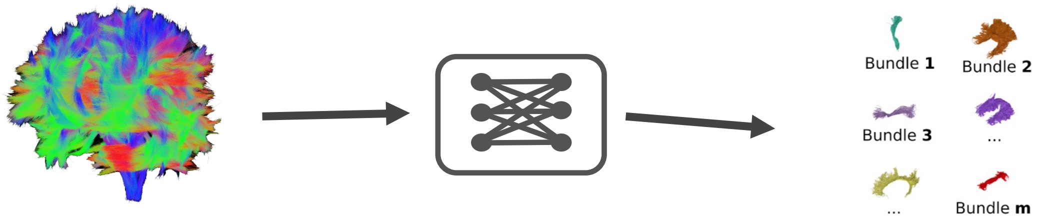
2. Sequence-based approaches



3. Global approaches

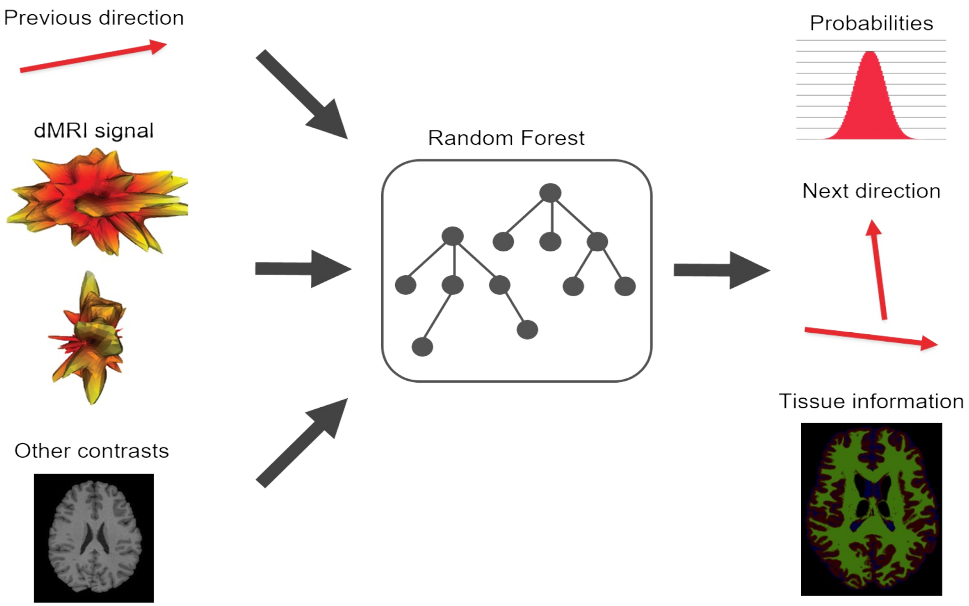


4. Streamline classification



ML-based local modeling

ML-based local modeling: RF-based local modelling

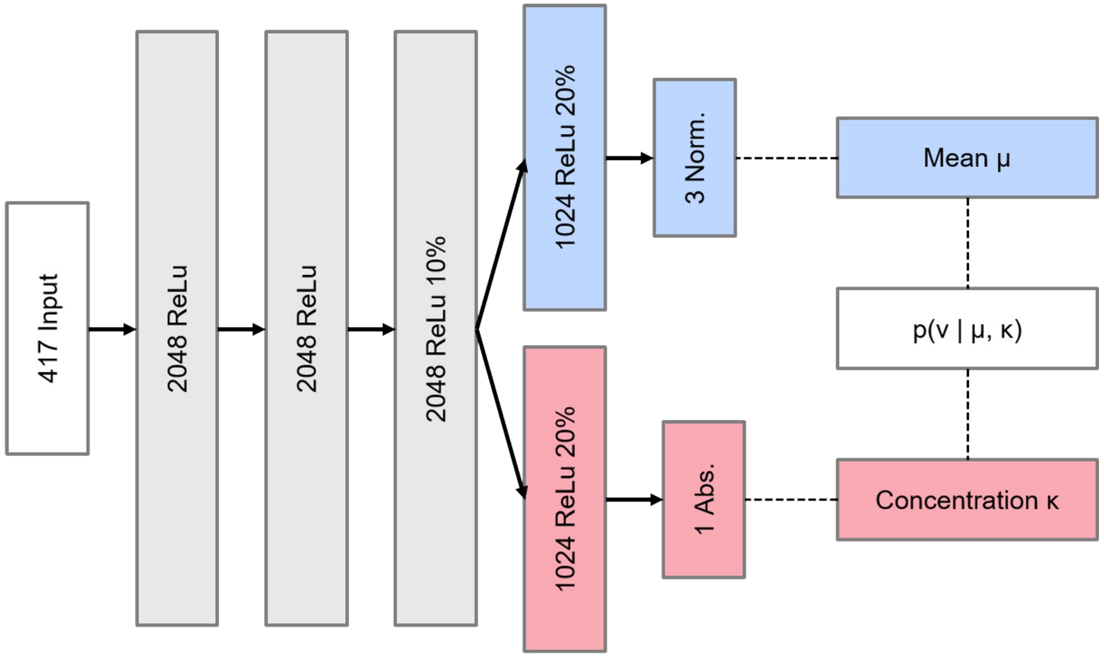


https://github.com/MIC-DKFZ/MITK-Diffusion/

1. Random forest classification
2. Enables probabilistic and deterministic tractography
3. Rather complicated neighborhood sampling and voting scheme

ML-based local modeling: Entrack

1. CNN-based
2. Deterministic regression of next direction
3. Estimation of the parameters of Fisher-von-Mises (FvM) distribution
   → *Entrack*
4. Directly process neighboring voxels



https://github.com/vwegmayr/entrack

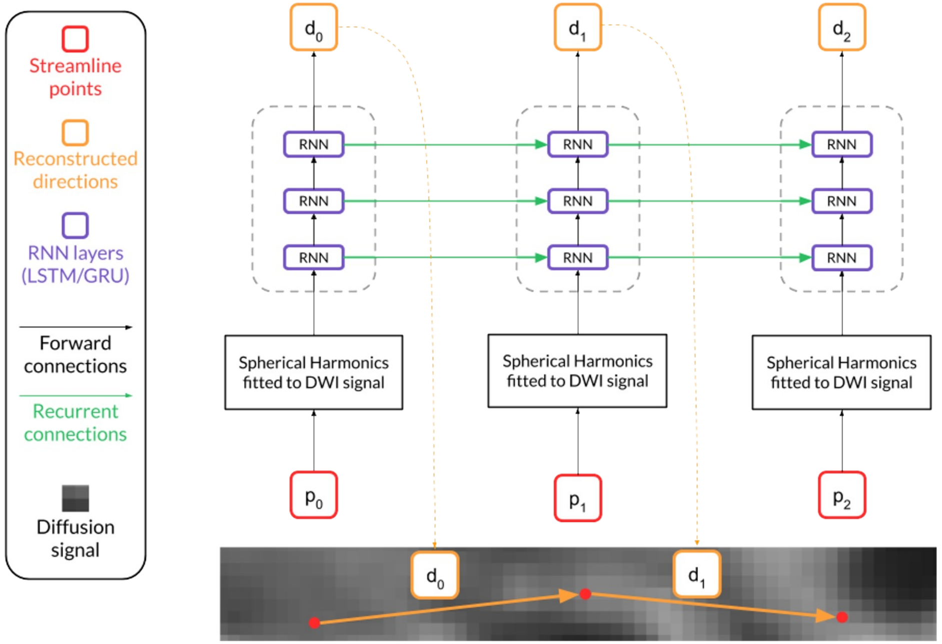
Wegmayr et al., "Entrack: A Data-Driven Maximum-Entropy Approach to Fiber Tractography", Pattern Recognition 2019

Performance: ISMRM 2015 Tractography Challenge Data

Model	Training Data	VB	IB	VC	OL	OR
RF (Neher)	5x HCP	23/25	94	52%	**59%**	37%
CNN (Wegmayr)	3x HCP	23/25	**57**	**72%**	16%	**28%**
Entrack (Wegmayr)	1x HCP	23/25	85	51%	23%	39%

Sequence-based approaches

Sequence-based modeling: Learn-to-track



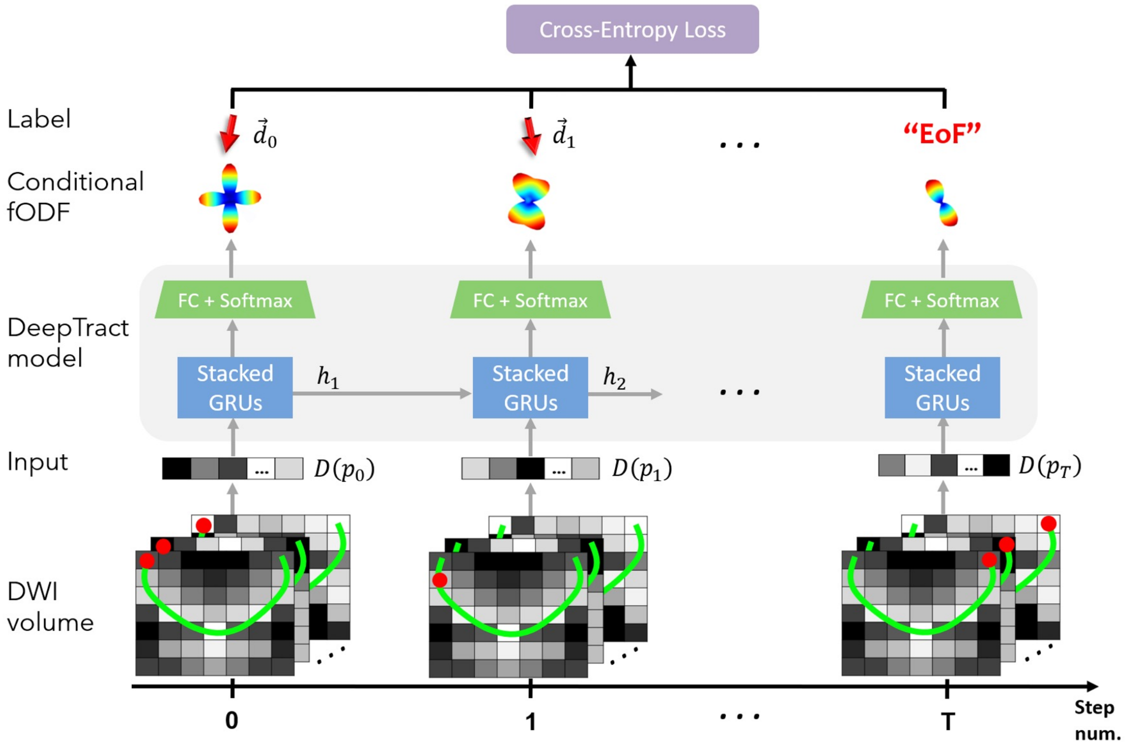
https://github.com/ppoulin91/learn2track
(Theano based)

1. RNN-based
2. Deterministic regression of next direction

Poulin et al., “Learn to Track: Deep Learning for Tractography”, MICCAI 2017

Sequence-based modeling: DeepTract

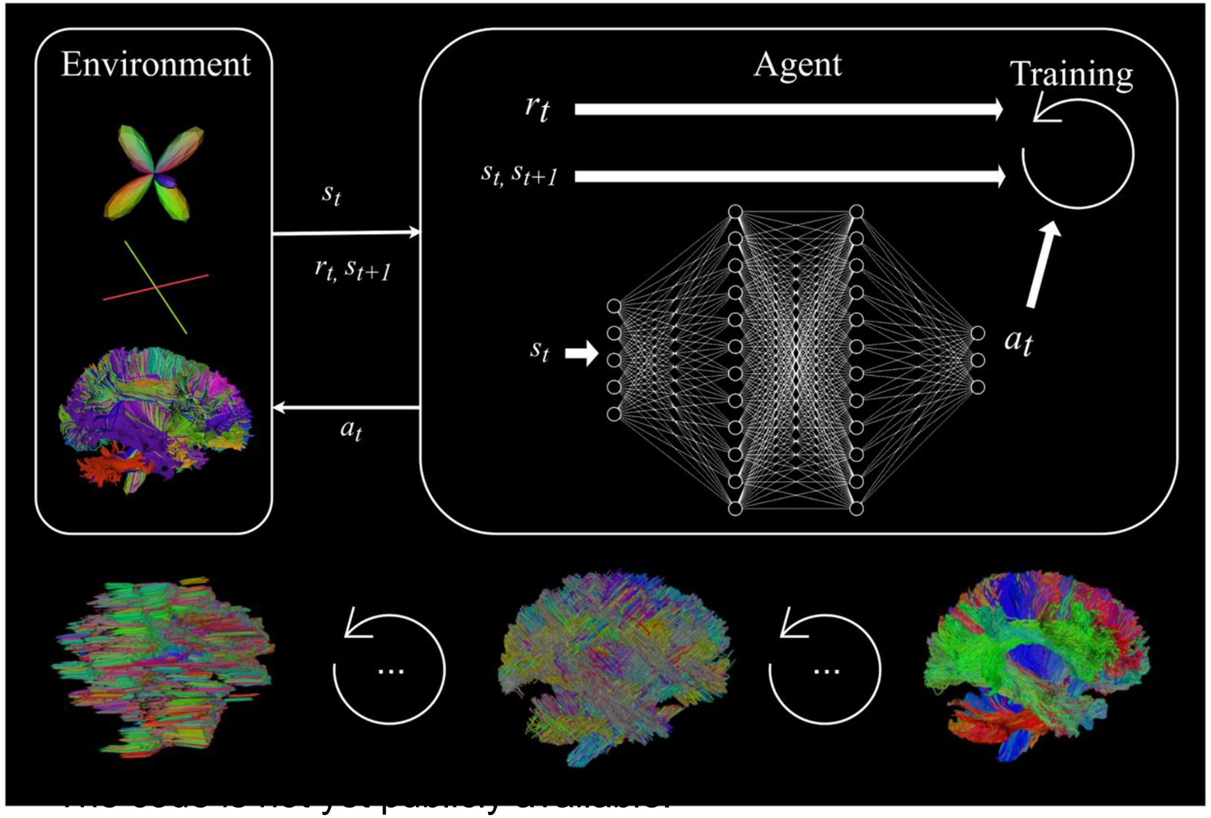
1. RNN-based
2. Formulated as classification problem similar to Neher et al.
3. Probabilistic determination of next direction



https://github.com/itaybenou/DeepTract

Benou et al., "DeepTract: A Probabilistic Deep Learning Framework for White Matter Fiber Tractography", MICCAI 2019

Sequence-based modeling: Track-to-learn



1. Unsupervised approach using reinforcement learning
2. Deterministic regression of next direction
3. State: 6-neighborhood signal, WM mask values, 4 previous steps
4. Reward based on alignment with the underlying fODF peaks as well as with the previous direction

Théberge et al., “Track-To-Learn: A general framework for tractography with deep reinforcement learning”, Medical Image Analysis 2021

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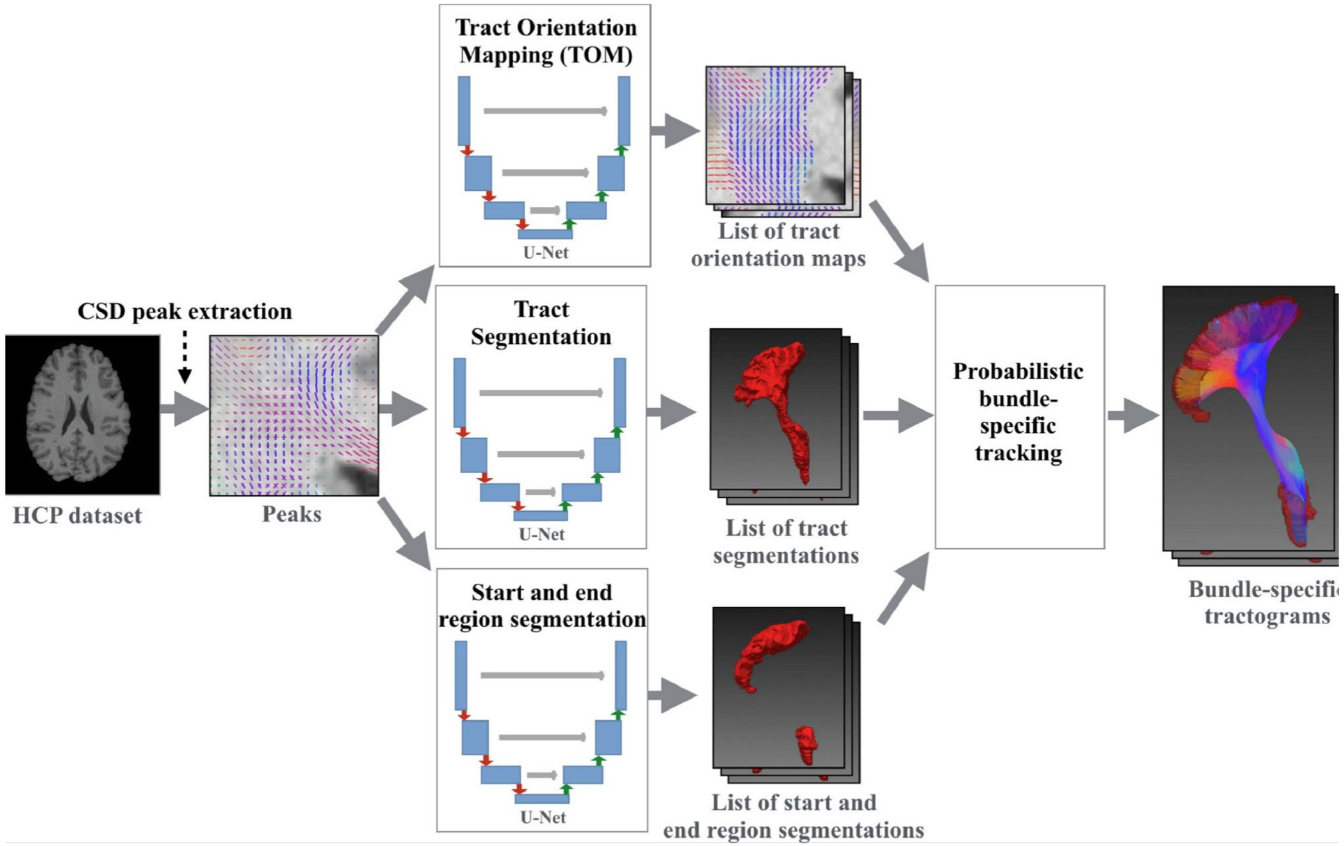
Learn-to-track (Poulin)	ISMRM phantom	23/25	130	42%	64%	35%
DeepTract (Benou)	ISMRM phantom	23/25	**51**	41%	34%	**17%**
Track-to-Learn (Théberge)	-	23/25	161	68%	56%	n/a

Global approaches

Global modeling: TractSeg

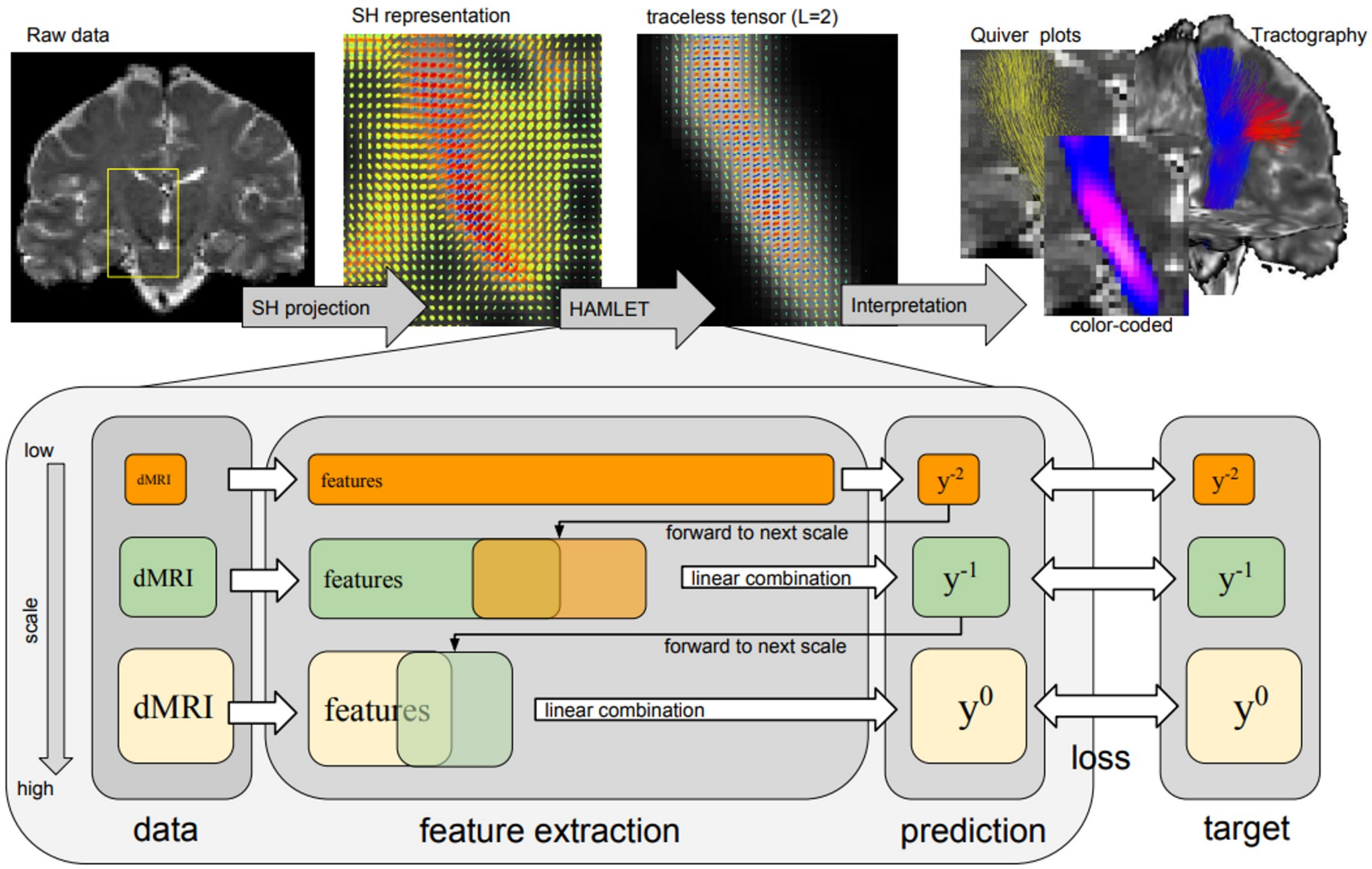
1. U-Net based segmentation of 72 tracts
2. Segmentation of tract endpoints
3. Computation of tract orientation maps (TOM)
4. Bundle-specific tractography



https://github.com/MIC-DKFZ/TractSeg/

Wasserthal et al., “TractSeg - Fast and accurate white matter tract segmentation”, Neuroimage 2018
Wasserthal et al., “Combined tract segmentation and orientation mapping for bundle-specific tractography”, Medical Image Analysis 2019

Global modeling: HAMLET



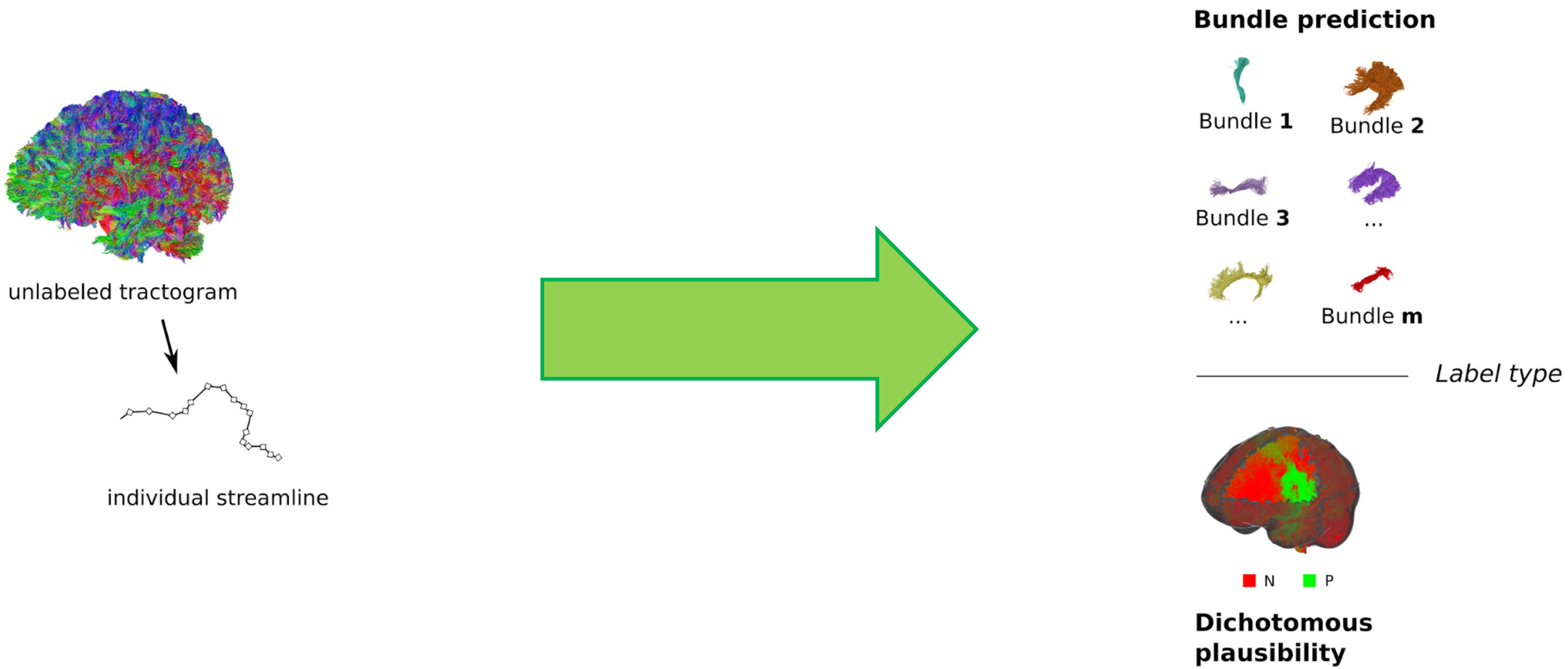
The HAMLET code is available from the authors upon reasonable request

1. Rotation Covariant Tract Estimation
2. Similar to a CNN but convolutions respect rotations in the way that if the input is rotated the output rotates accordingly
3. In theory allows lower model complexities
4. Tensor maps of 12 tracts that can be used for tractography

Reisert et al., “HAMLET: Hierarchical Harmonic Filters for Learning Tracts from Diffusion MRI”, ArXiv180701068 2018

Streamline classification

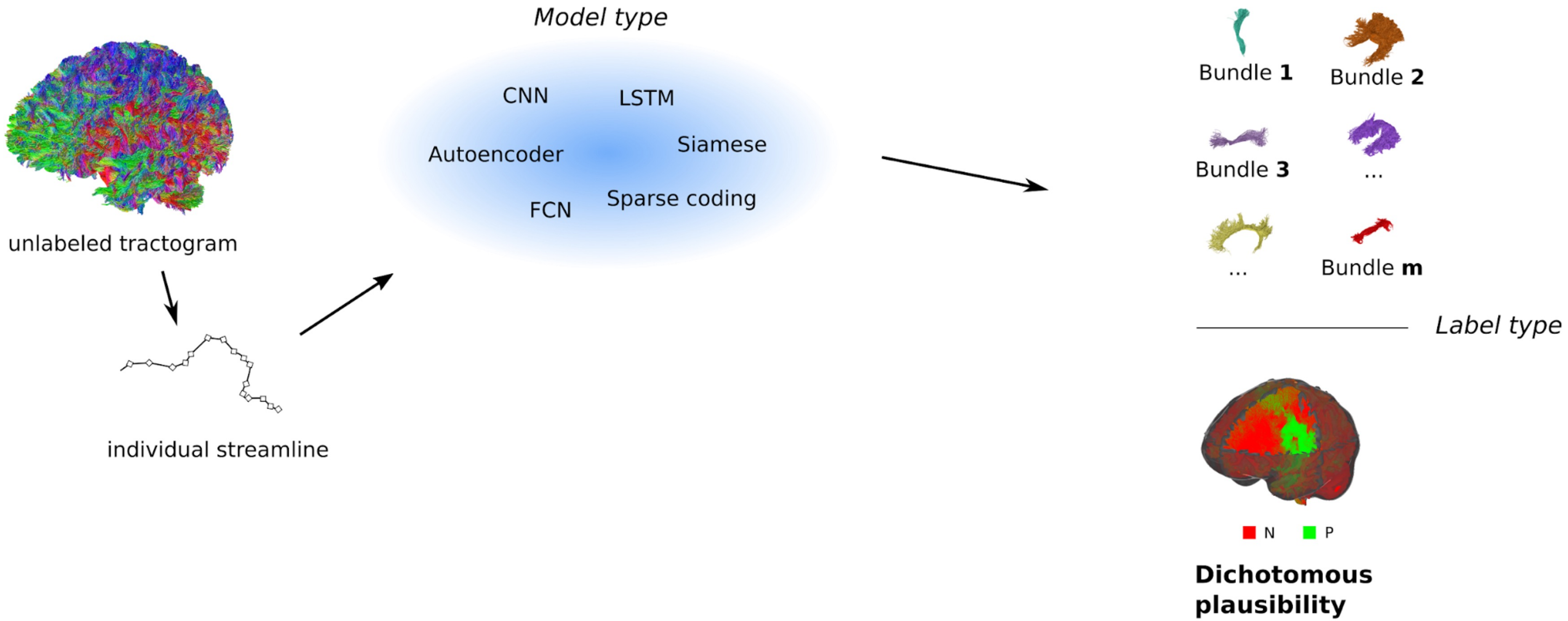
Streamline Classification



https://github.com/FBK-NILab/app-classifyber

Bertò et al., “Classifyber, a robust streamline-based linear classifier for white matter bundle segmentation”, Neuroimage 2020

Streamline Classification



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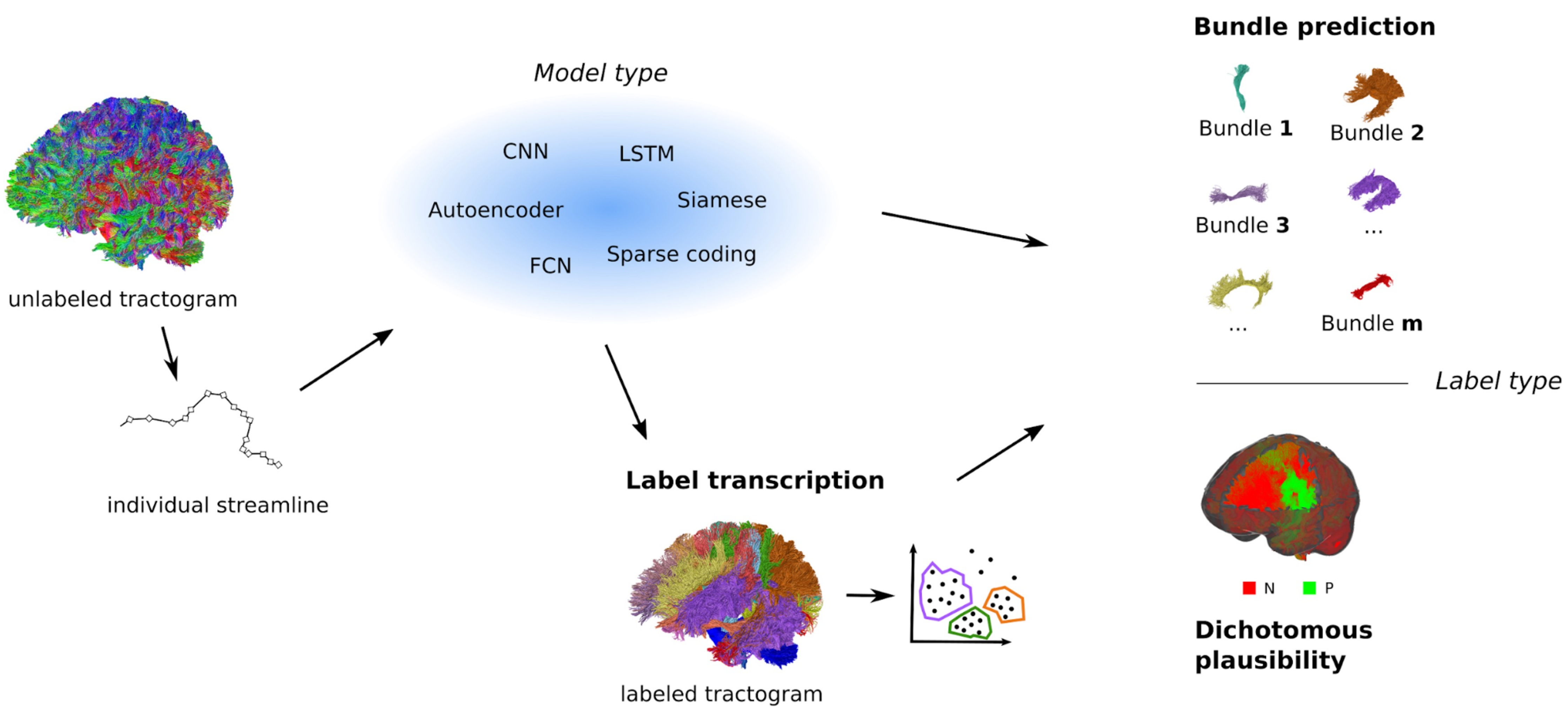
Streamline Classification



https://github.com/FBK-NILab/app-classifyber

Bertò et al., “Classifyber, a robust streamline-based linear classifier for white matter bundle segmentation”, Neuroimage 2020

Short conclusion

1. Local and sequence-based methods are currently only interesting from an academic point of view
2. Global approaches and streamline classification show real improvements over the state of the art
3. Main problem at the moment: training and validation data
    - Difficult to generate
    - Currently no comprehensive and also variable dataset in terms of type (in silico, in vivo, ex vivo), parameters (different scanners, acquisition settings) and subjects (number, age, healthy and diseased)

Bertò et al., “Classifyber, a robust streamline-based linear classifier for white matter bundle segmentation”, Neuroimage 2020

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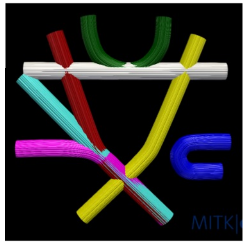

Some datasets

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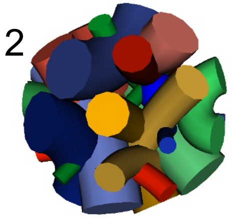

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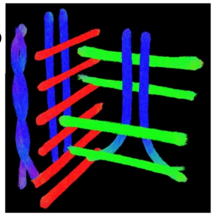

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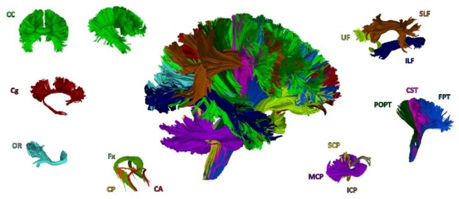

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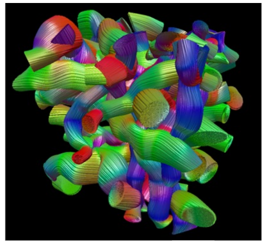

1	Simulated FiberCup	https://www.nitrc.org/frs/shownotes.php?release_id=2341
2	ISBI 2013 Challenge	http://hardi.epfl.ch/static/events/2013_ISBI/training_data.html#ground-truth-fiber-geometries
3	3D VoTEM	https://my.vanderbilt.edu/votem/
4	ISMRM 2015 Challenge	https://zenodo.org/record/572345 https://zenodo.org/record/579933 https://zenodo.org/record/1007149
5	Fiberfox random fiber phantoms	https://zenodo.org/record/2533250
6	IronTract Challenge	https://irontract.mgh.harvard.edu/
7	HCP-minor bundle dataset (40 subjects)	https://brainlife.io/pub/5e1de1371875e1ab6794cce5
8	TractSeg dataset (105 subjects)	https://zenodo.org/record/1088278
9	99 simulated brains (99 subjects)	https://inrepo01.inet.dkfz-heidelberg.de/record/156611?ln=en
10	TractoInferno (200 subjects)	https://openneuro.org/datasets/ds003900/versions/1.1.0

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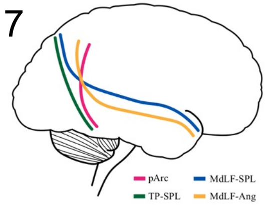

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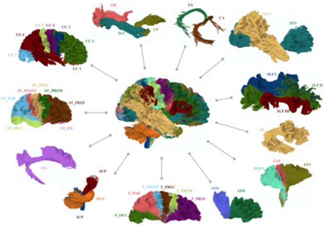

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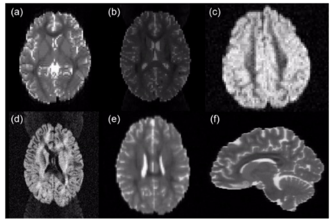

Thank you!

The MIC Team
www.dkfz.de/en/mic

- Fiberfox, ML Tractography, TractSeg GUI and much more in MITK Diffusion: https://github.com/MIC-DKFZ/MITK-Diffusion

- TractSeg as python package: https://github.com/MIC-DKFZ/TractSeg

- Semiautomatic segmentations of 72 tracts in 105 subjects: https://zenodo.org/record/1285152

- 99 simulated brains dataset: https://inrepo01.inet.dkfz-heidelberg.de/record/156611?ln=en