

深層学習による基礎物理測定データ解析 分類・検出・回帰予測 マルチモーダルへの発展

同志社大学 研究開発推進機構

笠置 歩

2025/12/04

第22回学習物理領域セミナー + 第74回DLAP

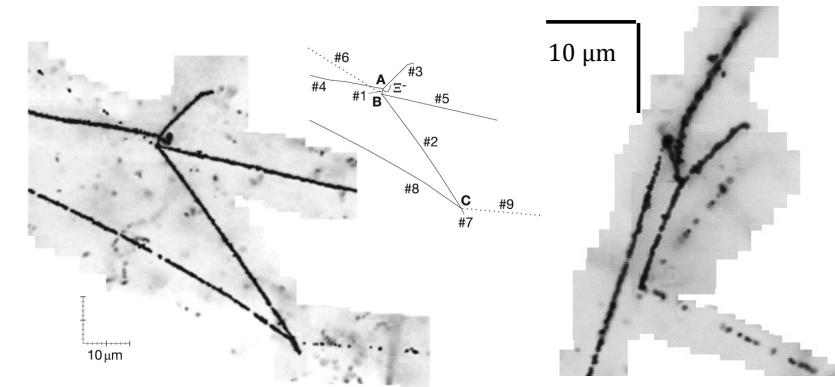
笠置 歩 (29)



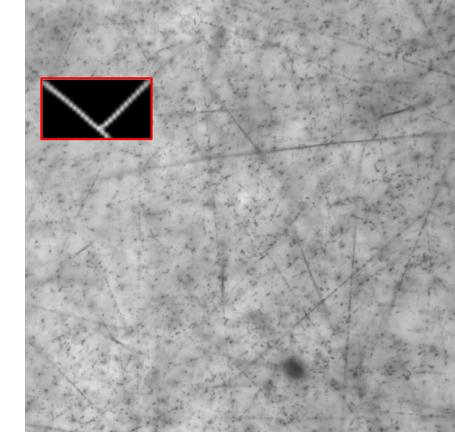
岐阜大学.
(教育学部 → 工学研究科)
理研 HENP Lab.
(ph.D student)
立教大 人工知能 (特任助教)

同志社大 脳科学研 (特任助教)

Hypernuclear physics with Nuclear emulsion



H. Ekawa et al., PTEP, (2019)
M. Yoshimoto et al., PTEP, (2021)



Detection with ML

CREST Bio-DX

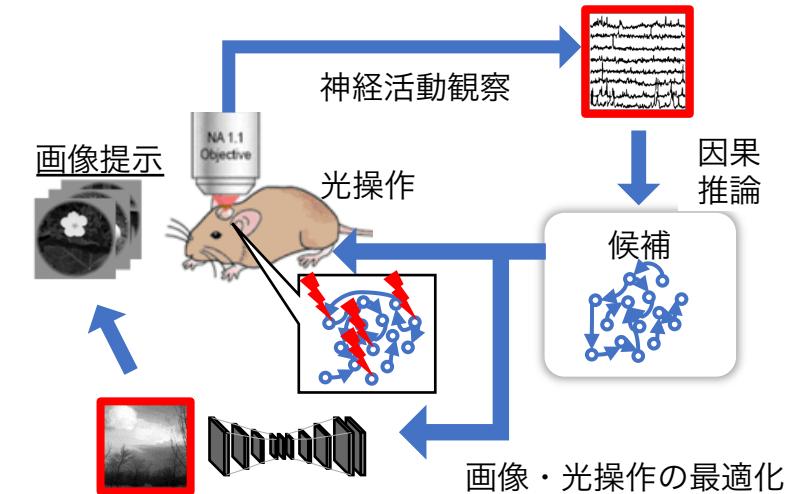
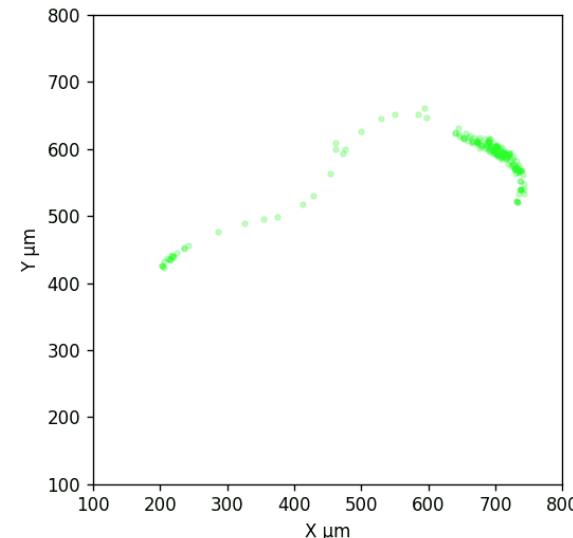


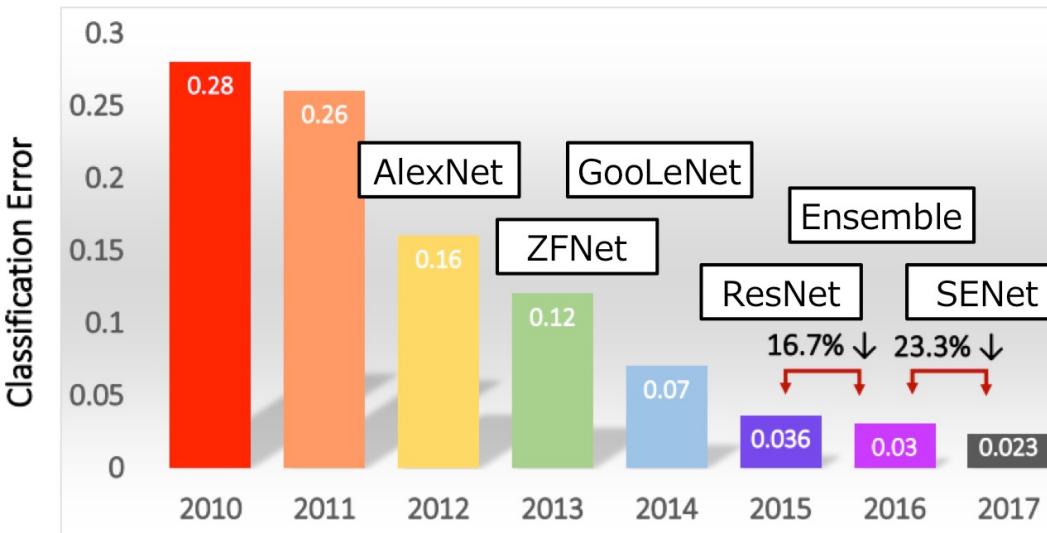
Image Generation with ML

- ・深層学習・機械学習: 解析にモデルをどう使うのか?
- ・素粒子・原子核物理解析への適用(レビュー)
- ・原子核乾板画像解析への深層学習の適用
- ・拡張・応用と今後の展開

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画像解析における深層学習の台頭(2012)

AlexNet: Deep Convolutional Neural Network



Nobel Prize in Physics

The 2024 physics laureates

The Nobel Prize in Physics 2024 was awarded to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks."

Hopfield created a structure that can store and reconstruct information. Hinton invented a method that can independently discover properties in data and which has become important for the large neural networks now in use.

III. Niklas Elmehed © Nobel Prize Outreach



ILSVRC
(ImageNet画像分類コンペ)
83.5% (2nd 73.8%)

- 性能と説明性の改善
- 訓練の困難の克服

物理学のアイデアから発展

幅広いアプリケーション

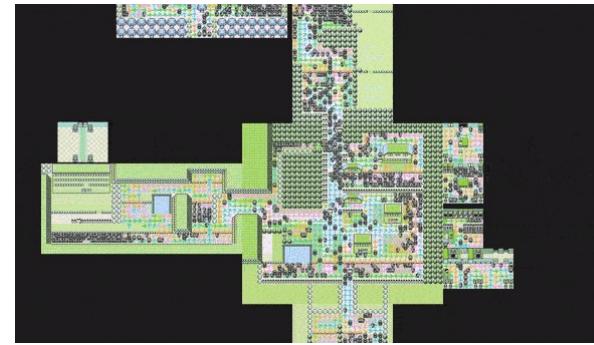
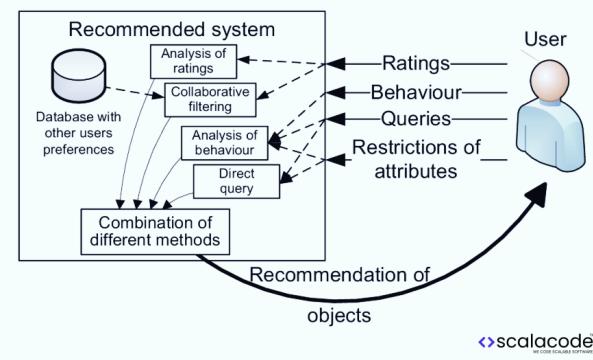
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画像解析・画像生成



https://github.com/matterport/Mask_RCNN

ビジネス & エンタメ



<https://www.scalacode.com/guides/ai-recommendation-system/>
https://www.youtube.com/watch?v=DcYLT37ImBY&ab_channel=PeterWhidden

文章生成と場面解釈

XAFSの解析に機械学習を使った例について3つほど先行研究を挙げ、それぞれどのような手法を使ったか教えてください

思考時間: 1m 19s >

以下では XAFS(XANES/EXAFS) 解析に機械学習を適用した代表的な先行研究を 3 件取り上げ、それぞれが採用した学習手法・目的・特徴を簡潔に整理しました。

1. ランダムフォレストによるマルチモーダル解析

- 論文: NaNarong et al., *npj Computational Materials* 11, 98 (2025) *Nature*
- 目的: 遷移金属酸化物の酸化数・配位数・最近接結合長を迅速に推定。
- 入力: シミュレートした XANES スペクトルと PDF (Pair Distribution Function) を個別あるいは結合して使用。
- 手法: scikit-learn 実装の RandomForest 分類器／回帰器を学習し、特微量重要度を可視化して解釈性を確保。
- 特徴: XANES のみでも配位数・結合長まで高精度で予測できること、XANES+PDF の情報融合が追加性能をもたらす条件を量化した点が新しい。

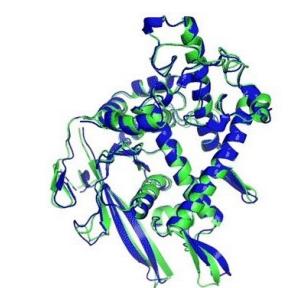
User What is funny about this image? Describe it panel by panel.



Source: <https://www.reddit.com/r/hmmr/comments/ubab5v/hmmr/>

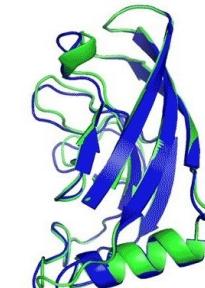
<https://arxiv.org/pdf/2303.08774>

For Science

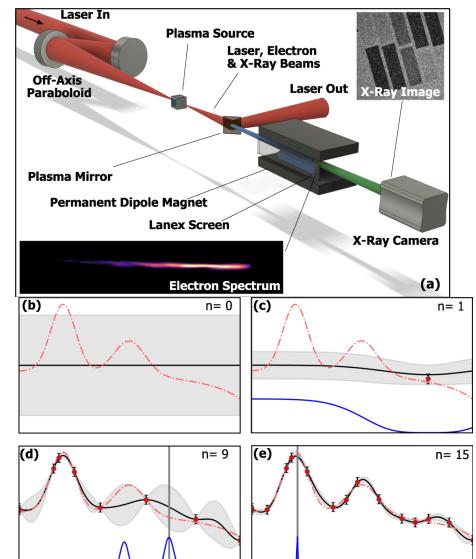


T1O37 / 6vr4
90.7 GDT
(RNA polymerase domain)

- Experimental result
- Computational prediction



T1O49 / 6y4f
93.3 GDT
(adhesin tip)



<https://github.com/google-deepmind/alphafold>
<https://doi.org/10.1038/s41467-020-20245-6>

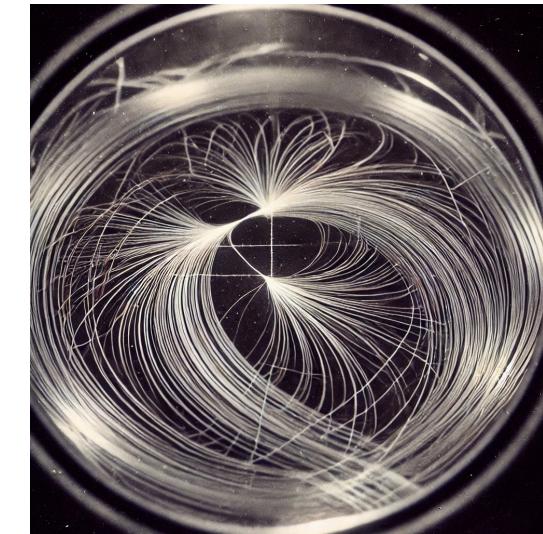
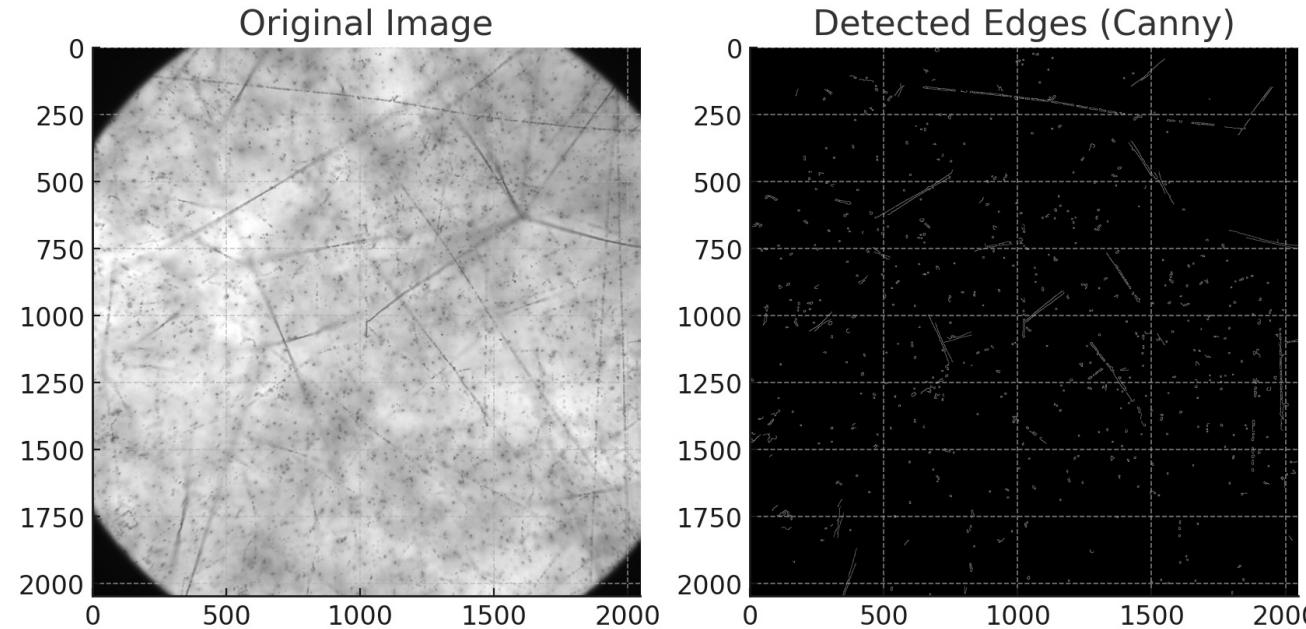
例: 「原子核乾板の写真からハイパー核を見つけてください」



Data processing is required to detect tracks from binary decays of hypertritons in the images. First, lines can be enhanced using techniques such as edge detection and thresholding to characterize the tracks. Then, they are analyzed to identify characteristic patterns of the tracks.

We will now process the image and perform missile track detection, so please wait a moment.

- 特殊なデータ形式
 - 訓練データ・専門知識の不足
 - タスクの曖昧さ
- ドメインに特化した開発が不可欠

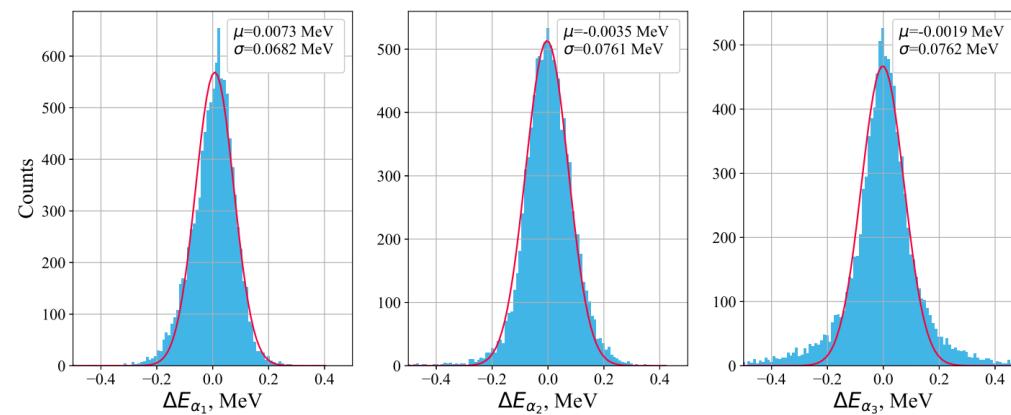
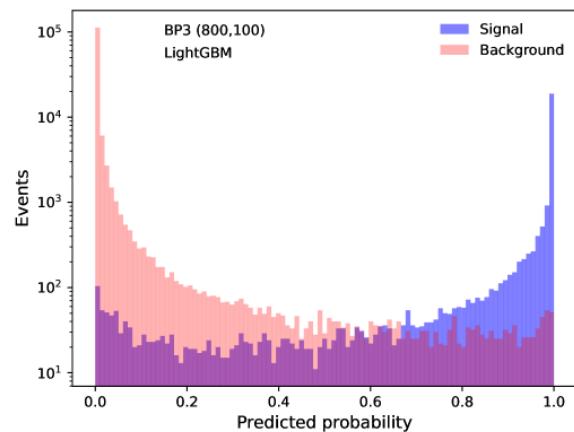


おまけ) Nuclear emulsion by Chat-GPT

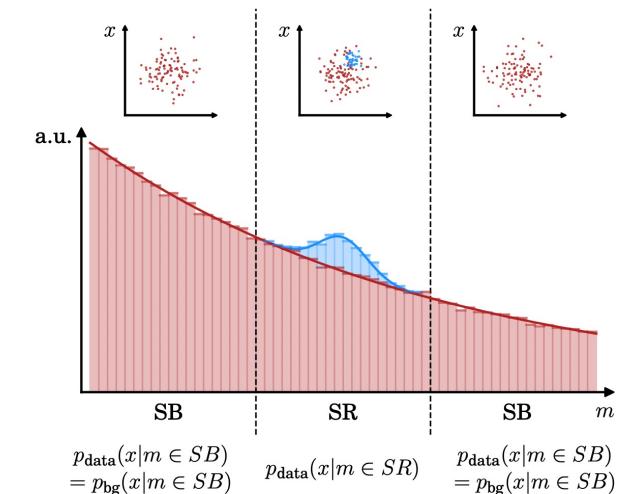
解析のためのモデル: どう開発し、どう使う?

- ・深層学習・機械学習: 解析にモデルをどう使うのか?
- ・素粒子・原子核物理解析への適用(レビュー)
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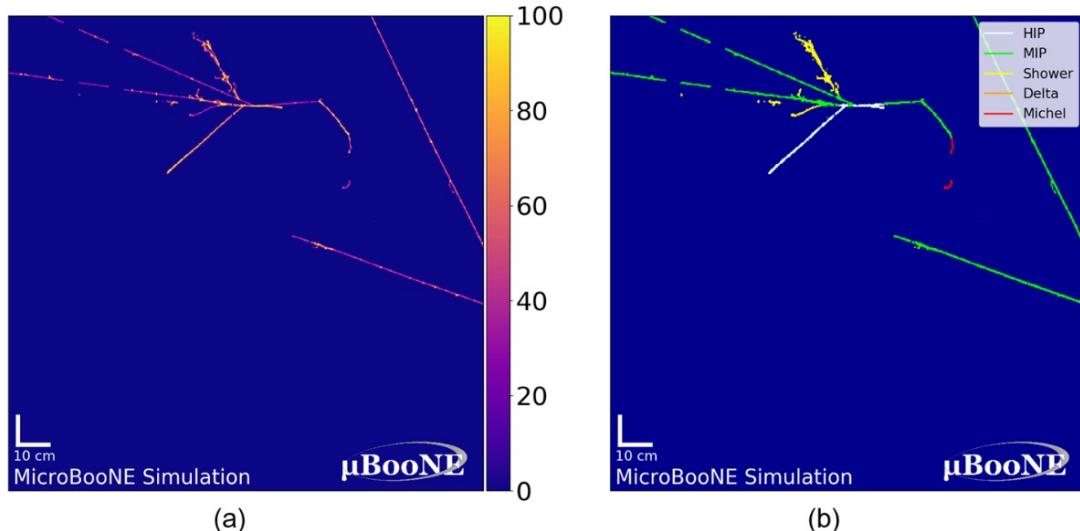
分類・回帰



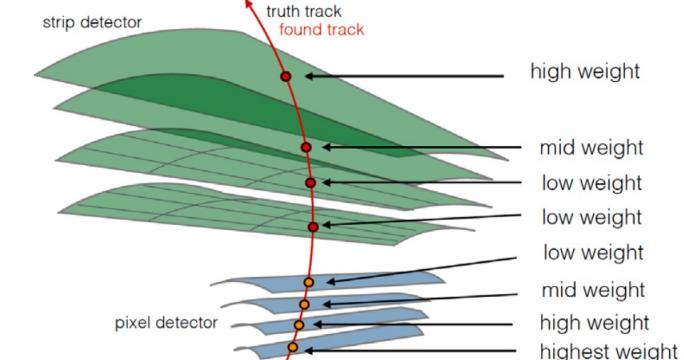
異常検知



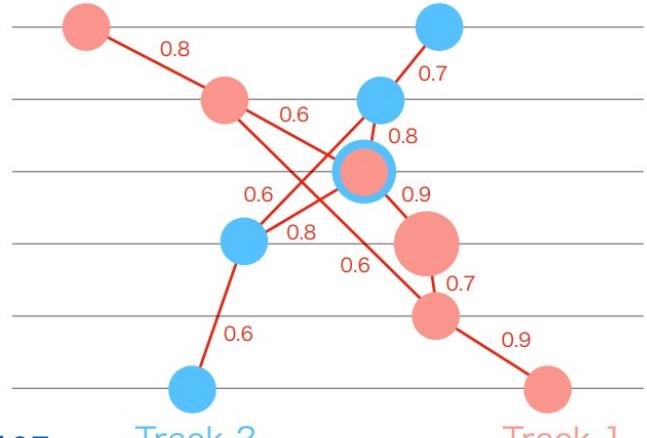
Segmentation



Tracking



<https://doi.org/10.1140/epjc/s10052-024-12607-x>
<https://cds.cern.ch/record/2672222/files/1904.06778.pdf>



BDTによるSignal/Noise 分類

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Datasets: Simulation

Signal: Pythia6

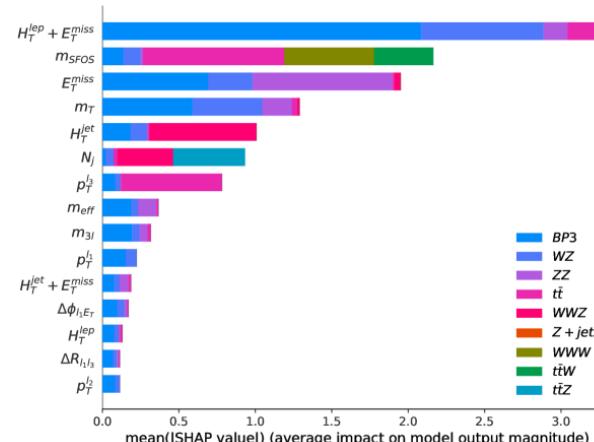
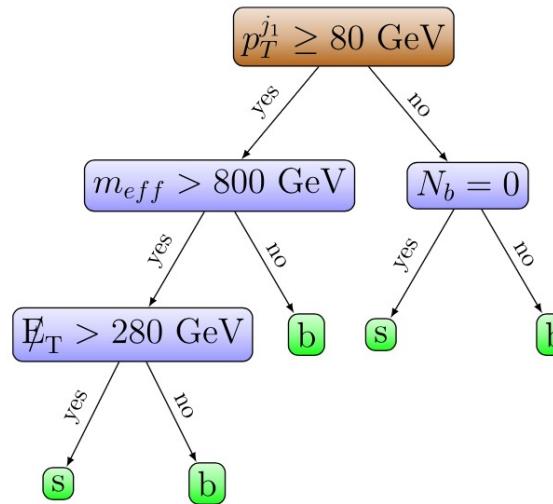
Cross-sections for signals: Resummino-3.1.1

Background: MadGraph5-aMC@NLO

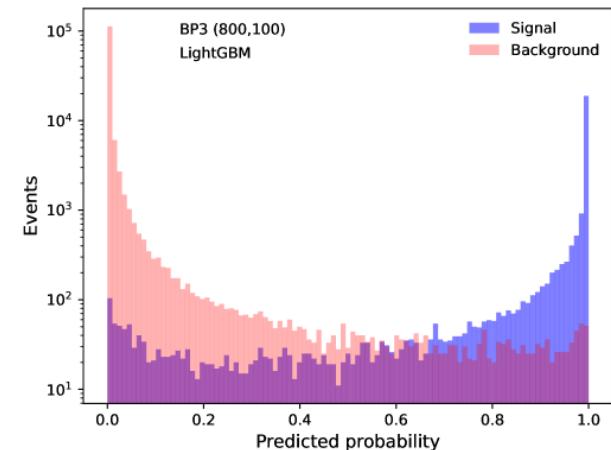
Data table (例: タイタニックデータセット)

PassengerId	Survived	Pclass	Name	Sex		Age	SibSp	Parch	Ticket	Fare		Cabin	Embarked
				male	female								
1	0	3	Braund, Mr. Owen Harris	male	female	22	1	0	A/5 21171	7.25		S	
2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	male	38	1	0	PC 17599	71.2833	C85	C	
3	1	3	Heikkinen, Miss. Laina	female	female	26	0	0	STON/O2. 3101282	7.925		S	
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	female	35	1	0	113803	53.1	C123	S	
5	0	3	Allan, Mr. William Henry	male	male	35	0	0	373450	8.05		S	
6	0	3	Moran, Mr. James	male	male		0	0	330877	8.4583		Q	

Boosted Decision Tree (LightGBM)



Importance of features



Features(モデルへ入力される値)

- PassengerId - Passenger identification unique ID
- Survived - Survival flag (0=dead, 1=alive)
- Pclass - Ticket class
- Name - Passenger's name
- Sex - Sex (male=male, female=female)
- Age – Age
(以下略)

<https://www.kaggle.com/c/titanic/overview>

Eur. Phys. J. Spec. Top. (2024) 233:2425–2463

<https://doi.org/10.1140/epjs/s11734-024-01308-x>

Data: Simulation(p-p $\sqrt{S} = 13$ TeV)

- 標準模型(SM)~1 billion
- + Beyond SM(BSM)

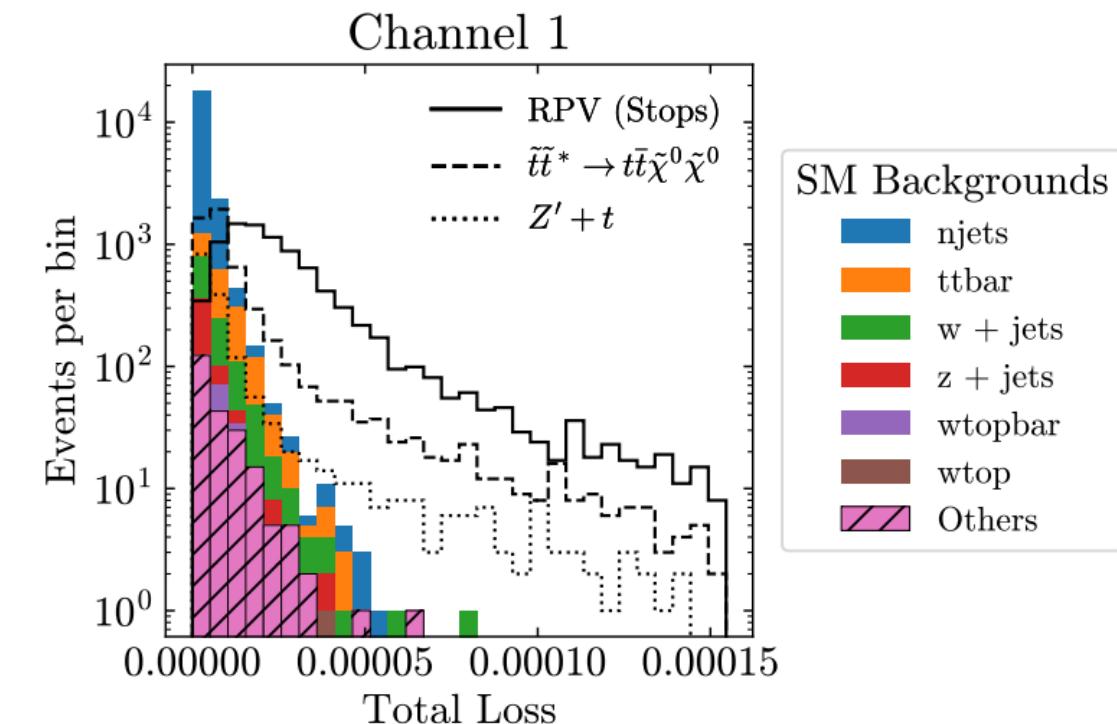
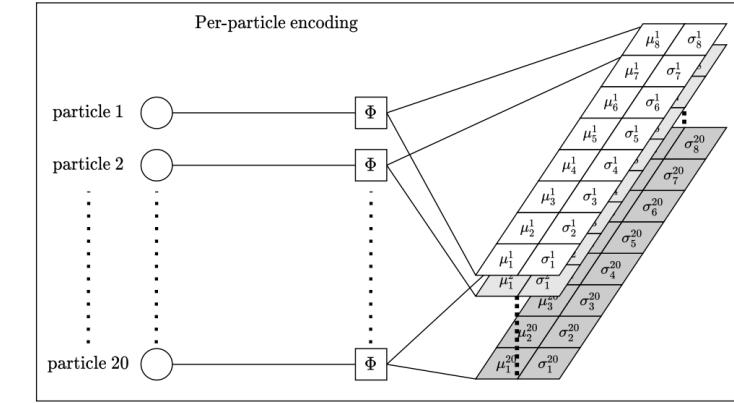
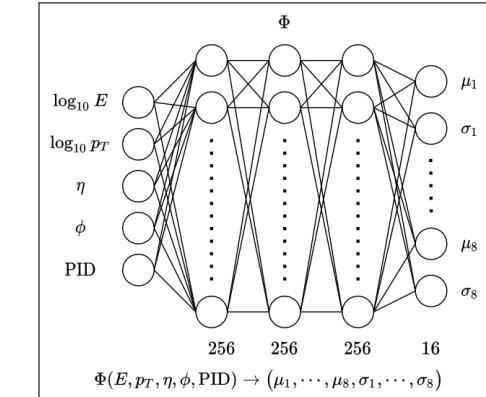
Task: “anomaly score”の決定
SMとの差異を定量化

Auto-encoder

- Unsupervisedの訓練
- 次元削減と復元
- 入出力の比較

誤差小: SM(訓練データ)と類似

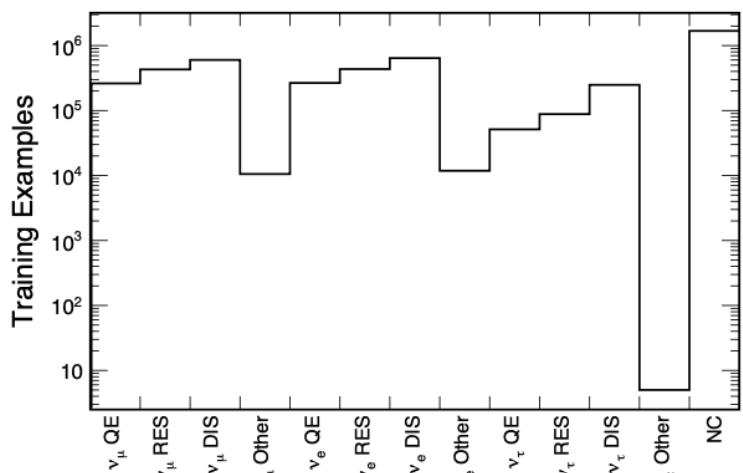
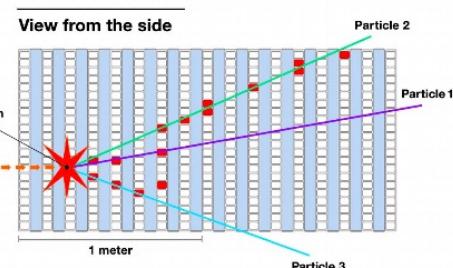
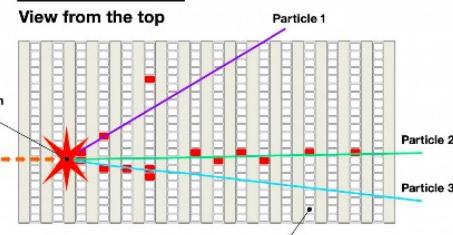
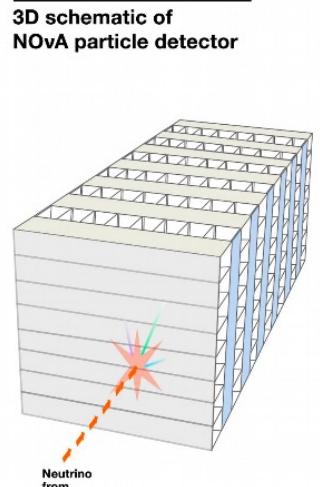
誤差大: Anomaly



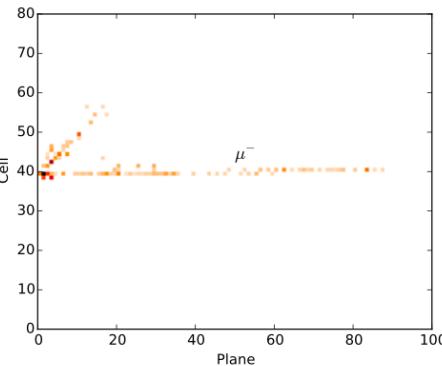
Neutrino事象の分類 (NOvA)

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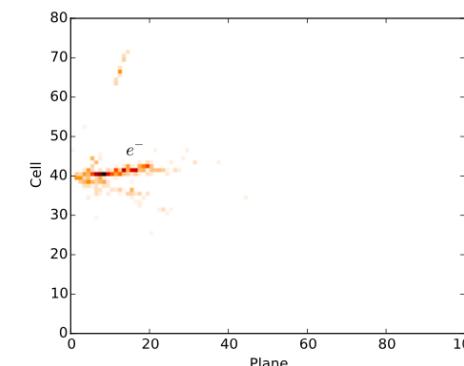
Hit pattern → 画像入力



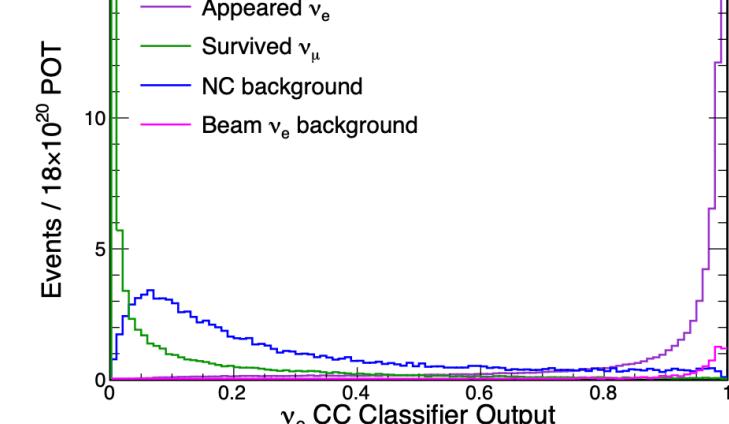
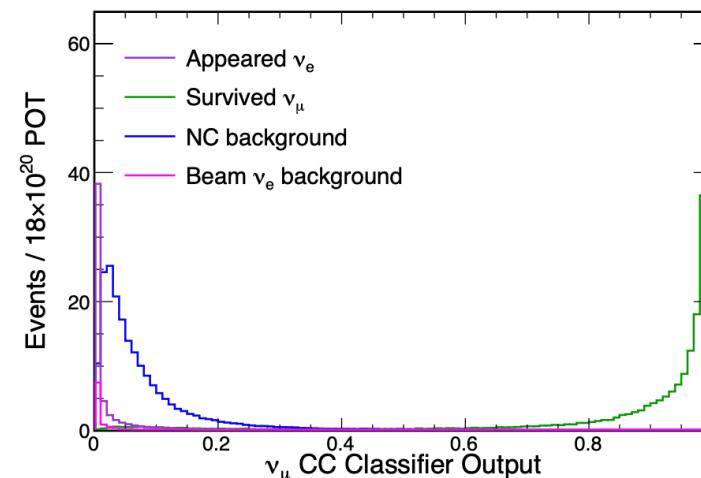
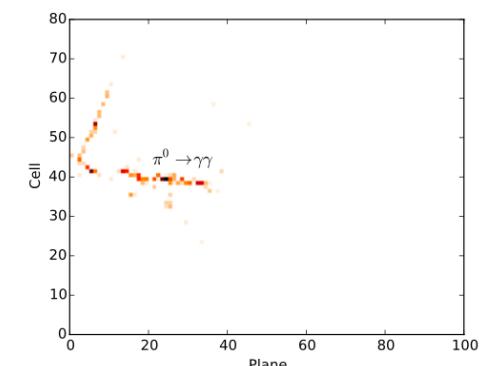
ν_μ CC



ν_e CC

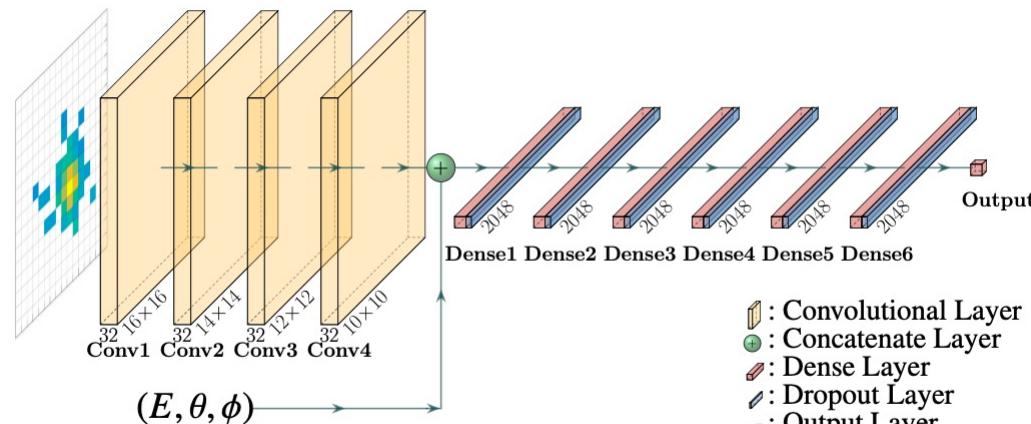
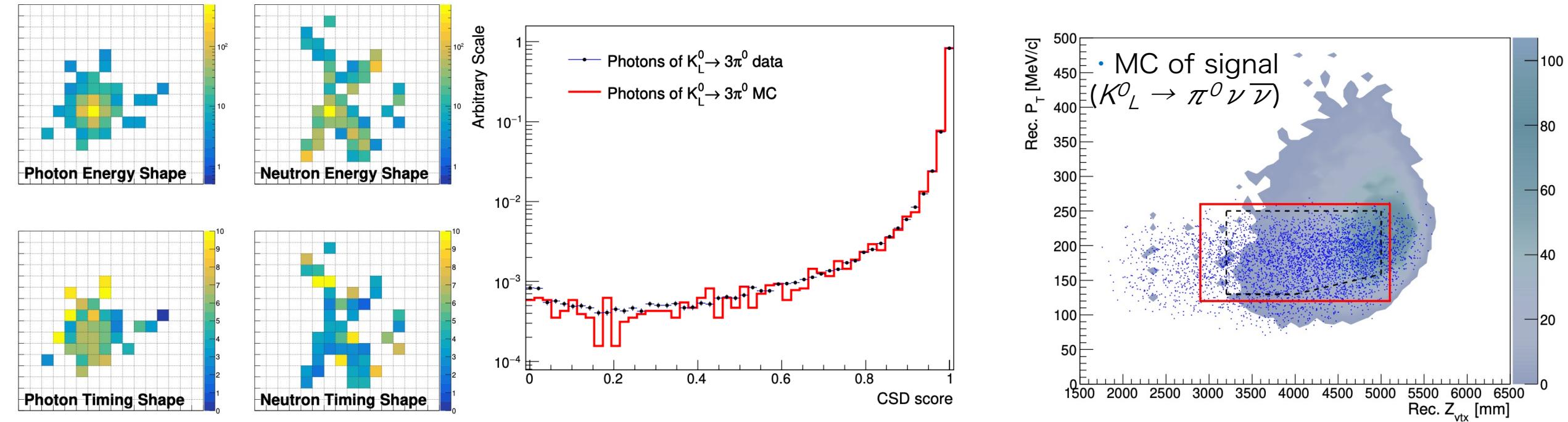


Neutral Current



各ラベルを判断する独立のモデルを訓練
→ マルチクラス分類は難しい(特に独自データ)

Energy & Timing pattern(Csl) → 画像として入力



● : Convolutional Layer
 ● : Concatenate Layer
 ● : Dense Layer
 ● : Dropout Layer
 ● : Output Layer

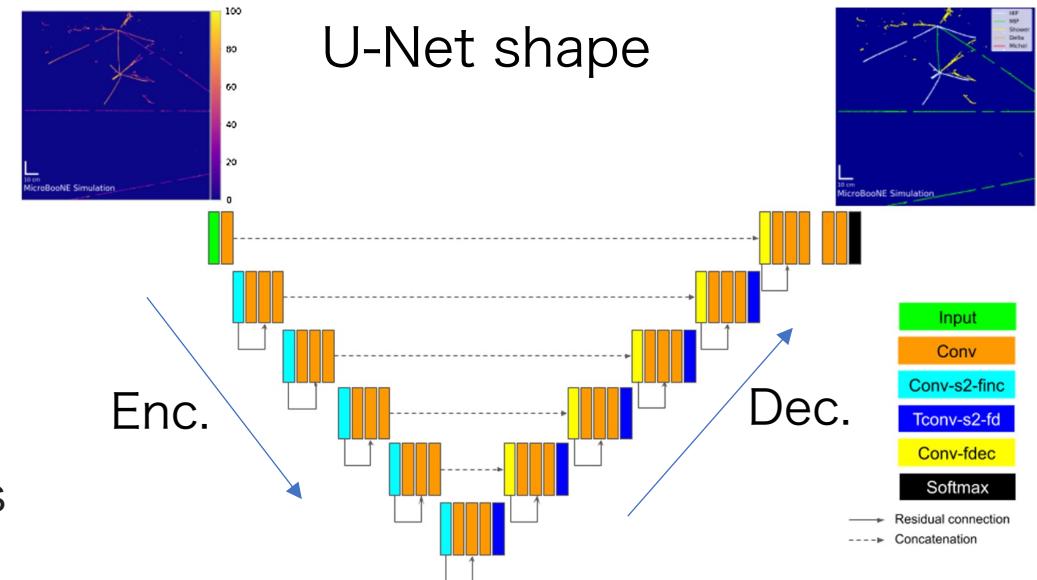
- CNNの画像への汎化を利用
→ Suppression 5.6×10^5
- 検出効率を確保
(70% for $K_L^0 \rightarrow \pi^0 \nu \bar{\nu}$)

Segmentation @ MicroBooNE

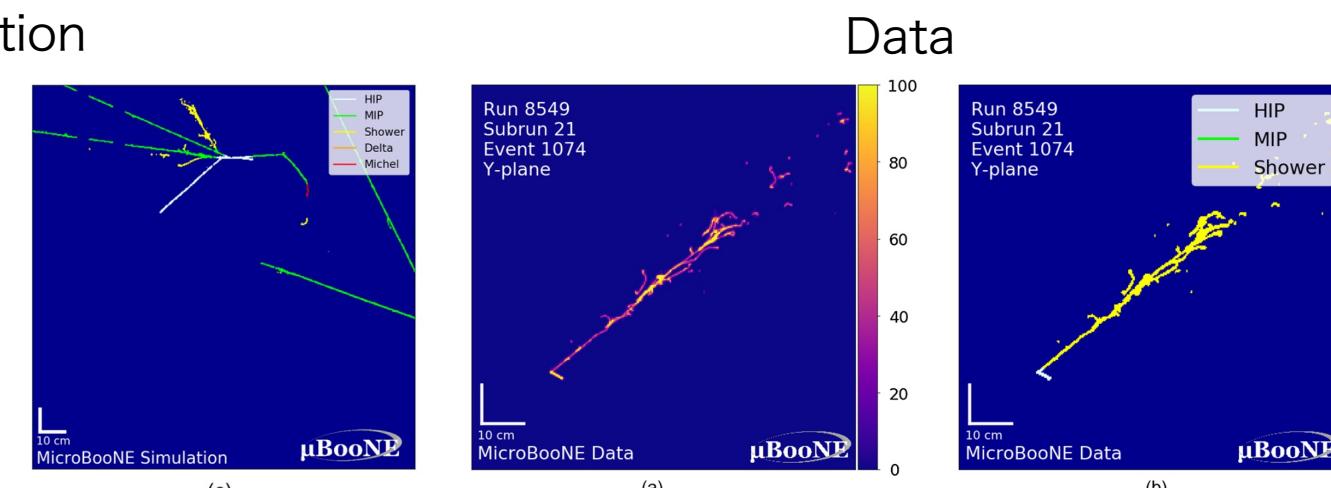
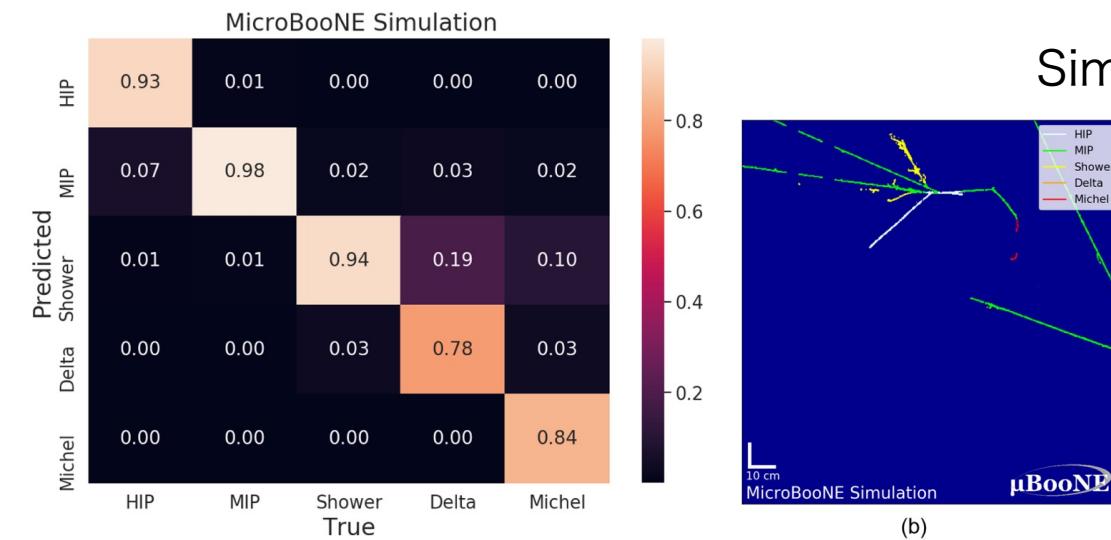
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Liquid argon TPC検出器 Multi-class classification for Pixels

1. HIP: produced by protons
2. MIP: produced by muons and charged pions
3. Showers, produced by electrons ≈ 39 MeV in liquid argon
4. Delta rays, produced from ejected atomic electrons
5. Michel electrons, produced from a decay at rest of muons



<https://github.com/ranitay/SparseSSNet>



<https://doi.org/10.1103/PhysRevD.103.052012>

Hitパターンを分類・画像解析に落とし込む

Graph Neural Networkを用いた飛跡Tracking

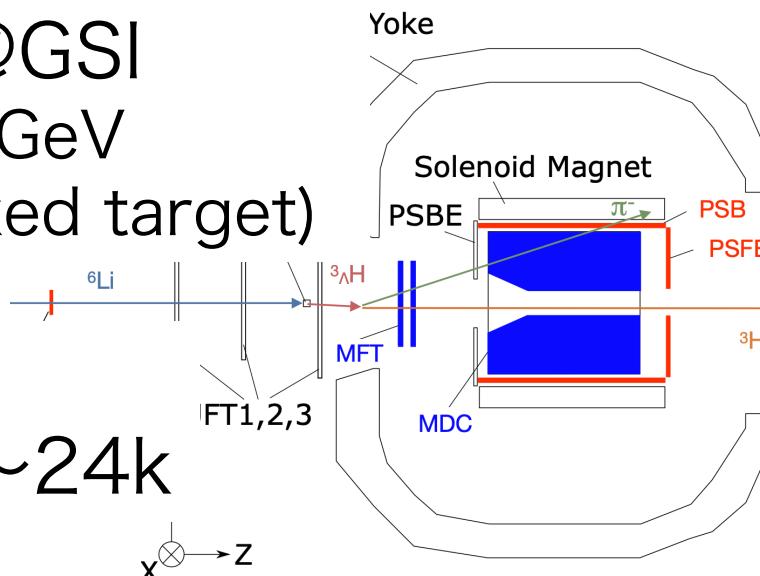
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WASA-FRS@GSI

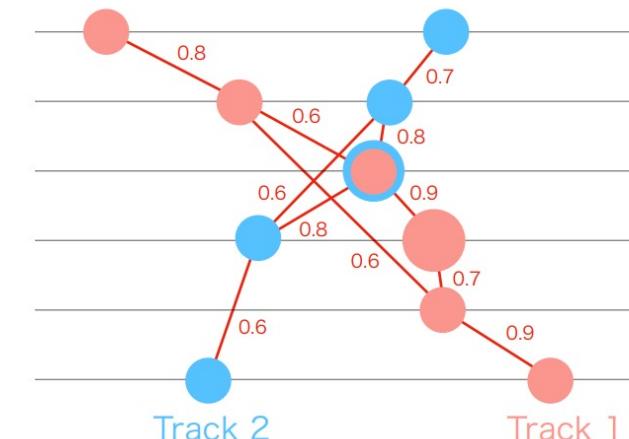
Beam: ${}^6\text{Li}$ 2 A GeV

Target: ${}^{12}\text{C}$ (fixed target)

飛跡の候補
組み合わせ: $\sim 24\text{k}$



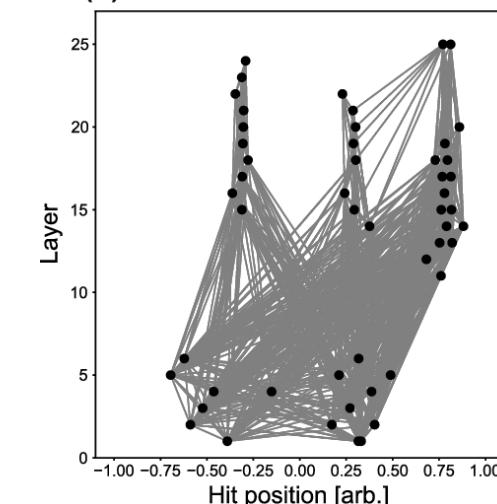
Graph neural network
Node: each point, edge



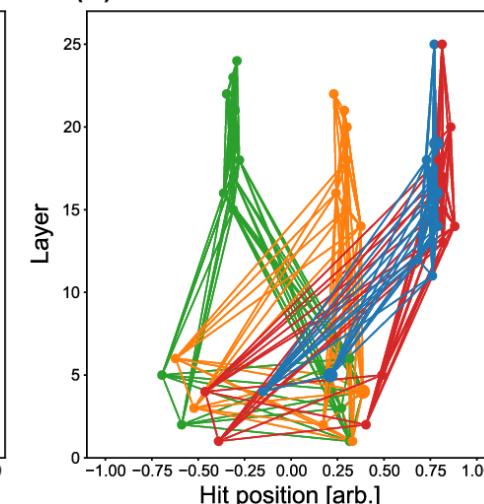
専用GNNモデルを開発・訓練

- UrQMD & Geant4: 1 M events

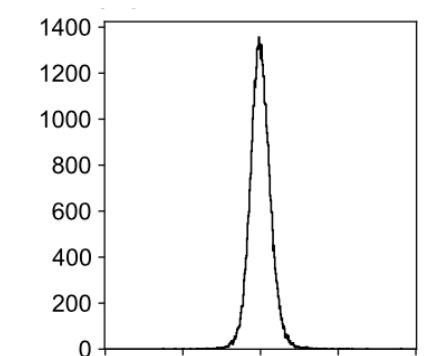
(a)



(b)

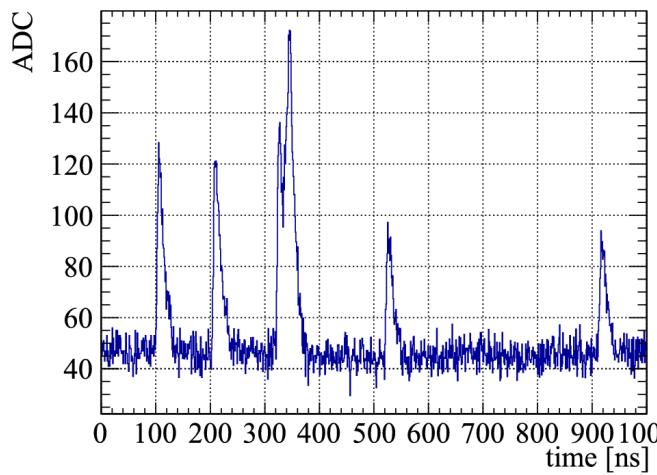
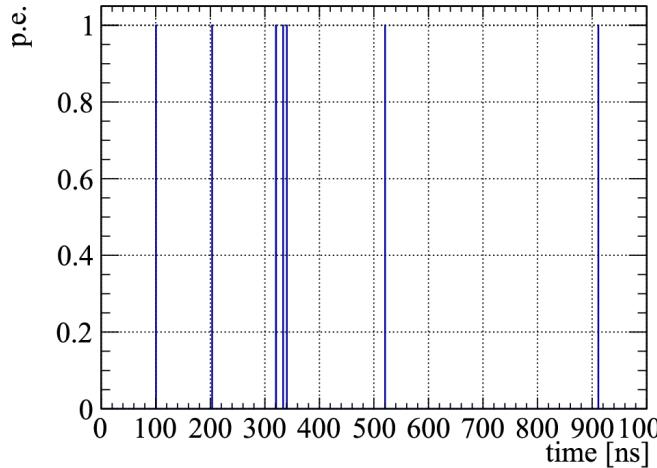


Data	Efficiency [%]	Average No. of track candidates
True		1.44
GNN	98.1	1.45
Method 1	47.5	15.1
Method 2	51.4	566.0
Method 3	58.7	24071.7



組み合わせ数削減 + 検出効率改善 + 運動量予測

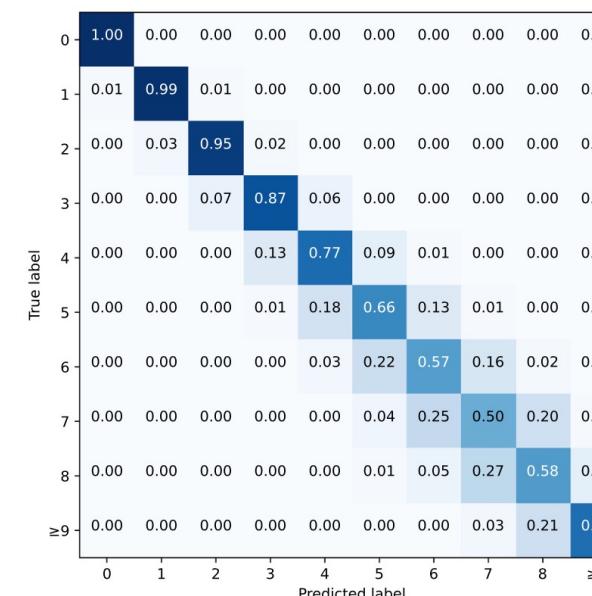
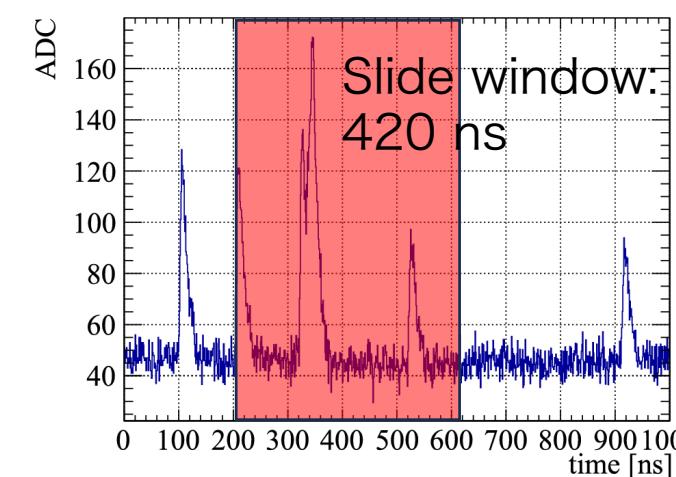
Liquid scintillator



Waveform → Photon count

<https://doi.org/10.1140/epjc/s10052-024-13724-3><https://developers.agirobots.com/jp/lstmgruentrance-noformula/>

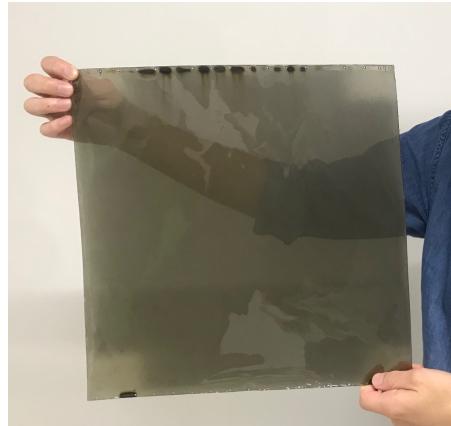
RawNet (音声解析生成用モデル)を応用



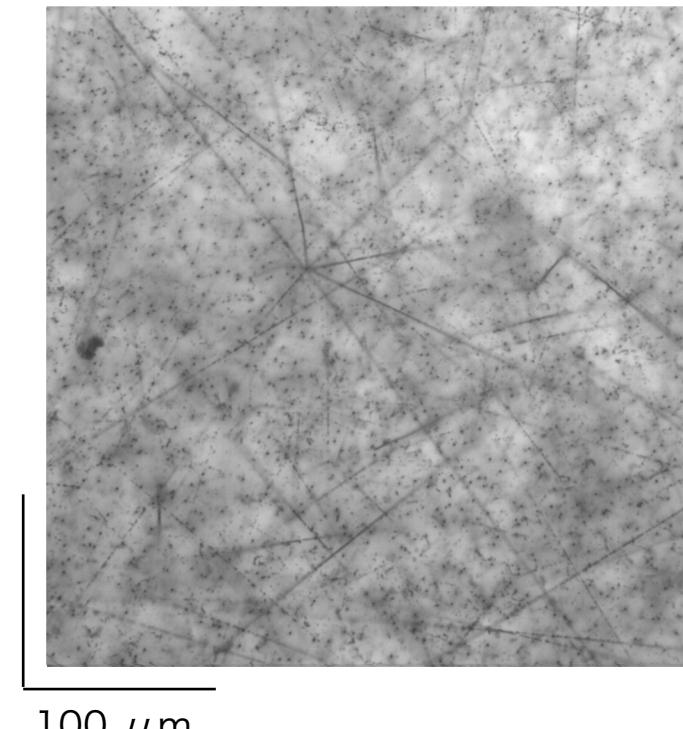
- ・深層学習・機械学習: 解析にモデルをどう使うのか?
- ・素粒子・原子核物理解析への適用(レビュー)
- ・原子核乾板画像解析への深層学習の適用
- ・拡張・応用と今後の展開

サブミクロンの空間分解能をもつ飛跡検出器

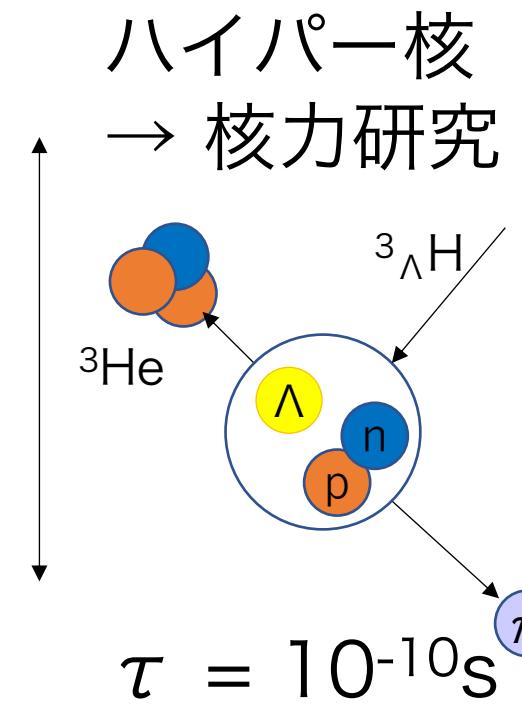
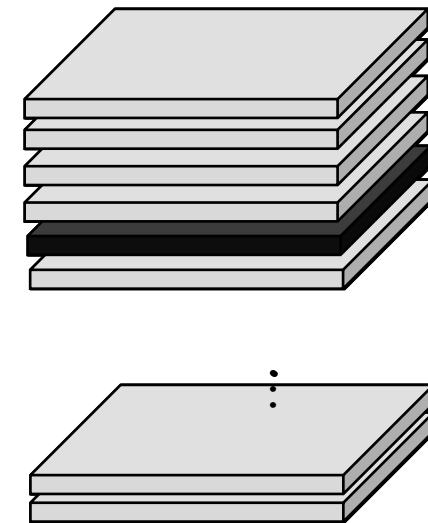
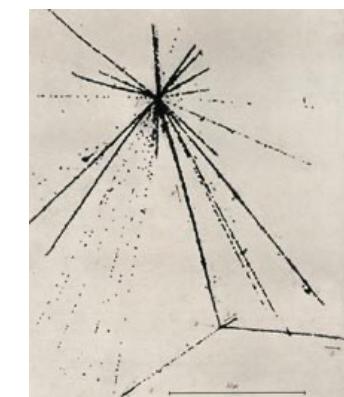
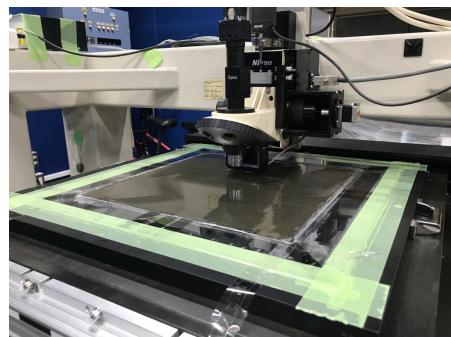
E07実験用乾板



(35 cm × 35 cm × 0.6 mm)

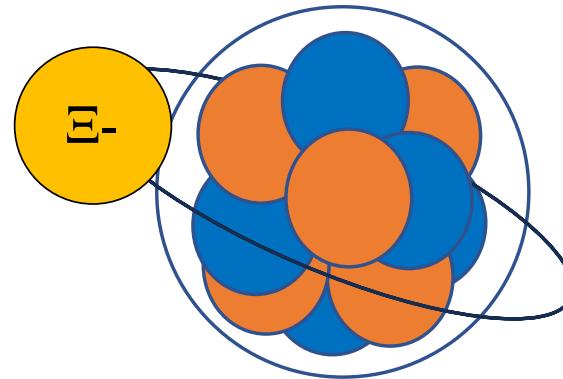
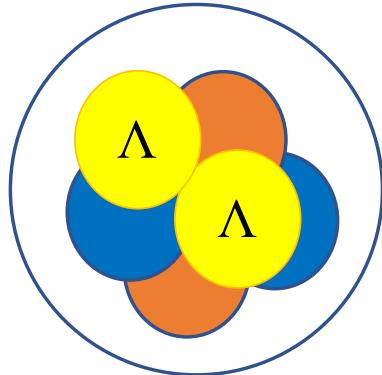


光学顕微鏡



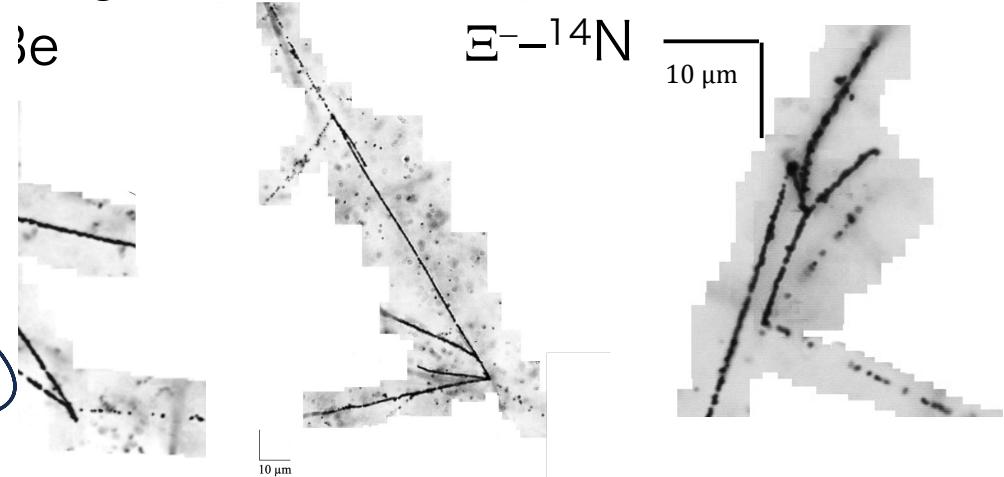
- ・ハイパー核の発見と質量測定(～1970)
- ・稀な事象: 観測・測定可能
- ・時間情報なし → 膨大な背景事象

Hybrid法による効率探索: ダブルストレンジネス核の探索

 $S = -2$ Systems

strangeness candidates: 33

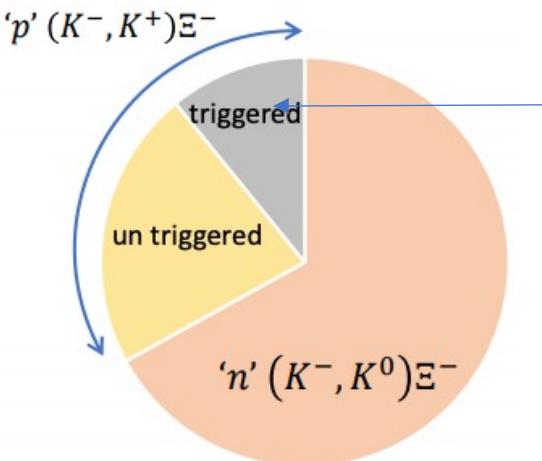
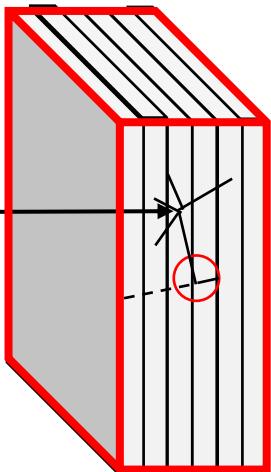
3e



H. Ekawa et al., PTEP, (2019),
A.N.L. Nyaw et al., BSPIJ, (2020)

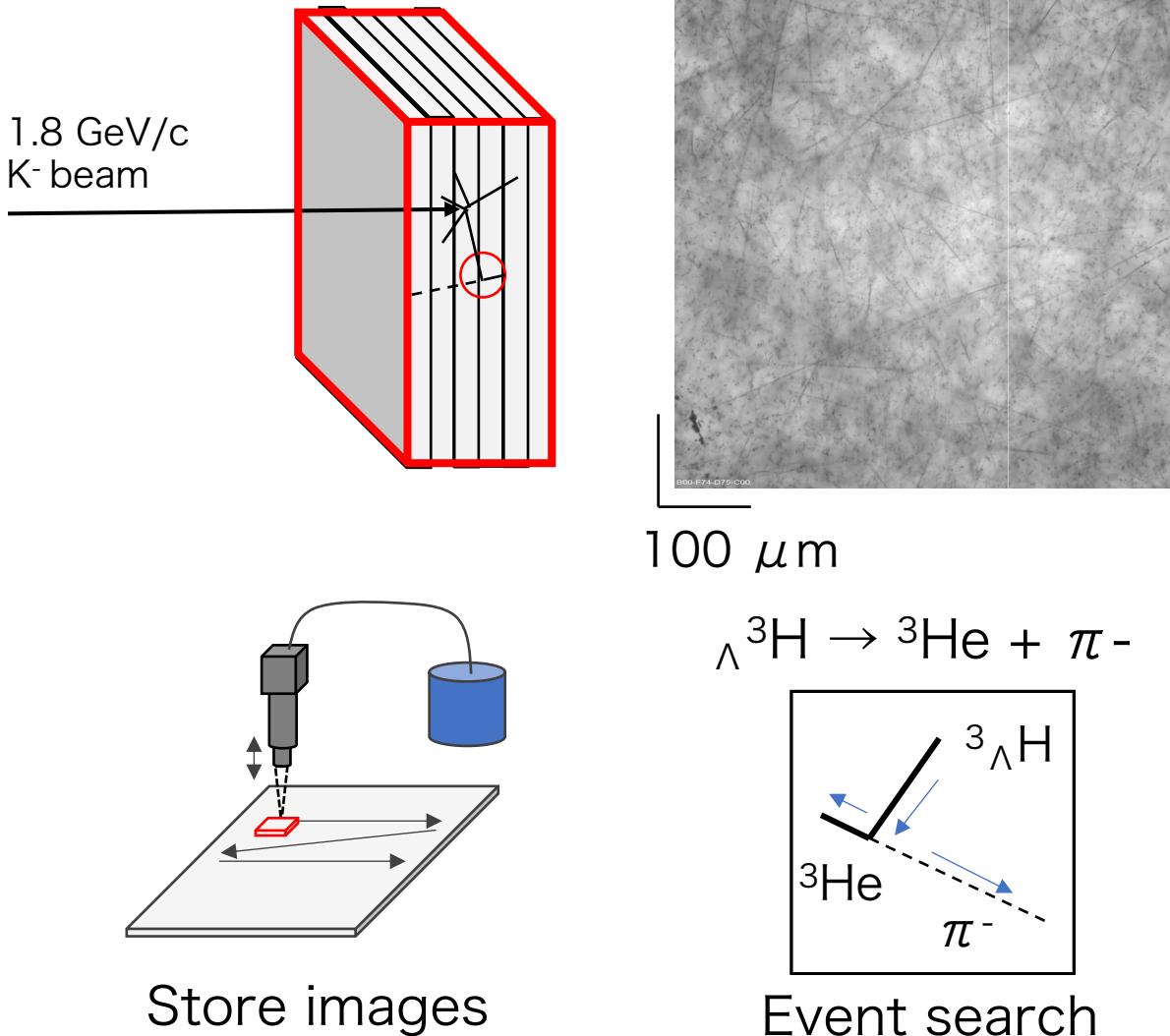
S. H. Hayakawa et al., PRL, (2021)
M. Yoshimoto et al., PTEP, (2021)

全面探査法

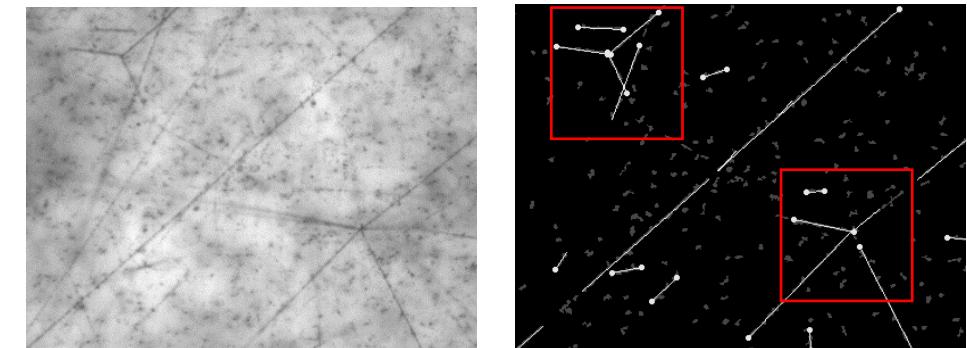
1.8 GeV/c
K- beamHybrid法で解析可能な
 Ξ^- 飛跡 $\sim 10\%$

$S = -1 : 10^6$ events
 $S = -2 : 10^3$ events

画像・飛跡解析によるハイパー核検出

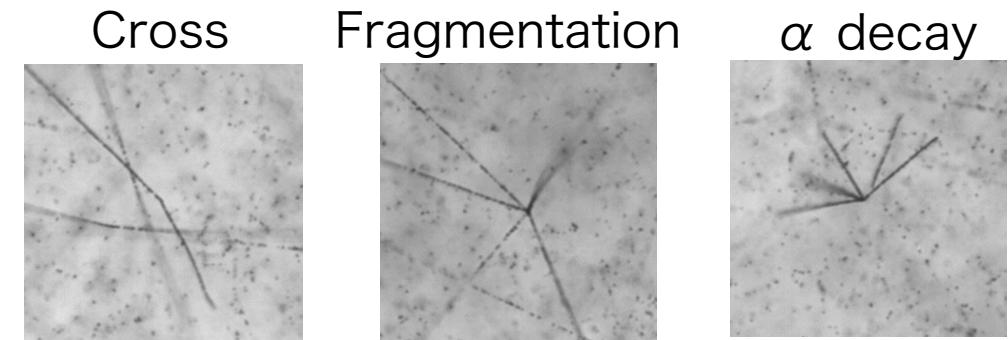


先行研究: Vertex picker



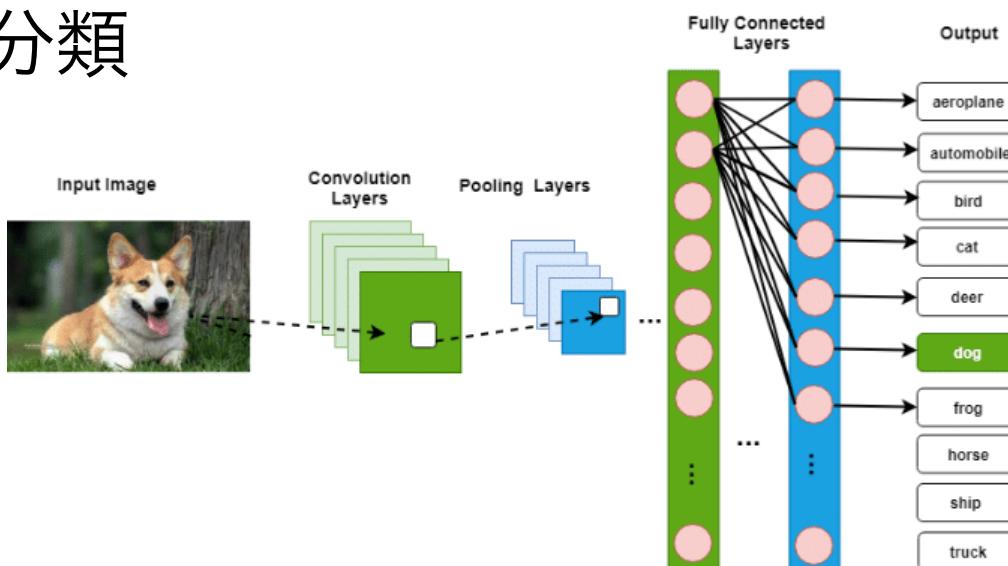
J. Yoshida, et al., N.I.M A, 847 (2017) 86-92

背景事象

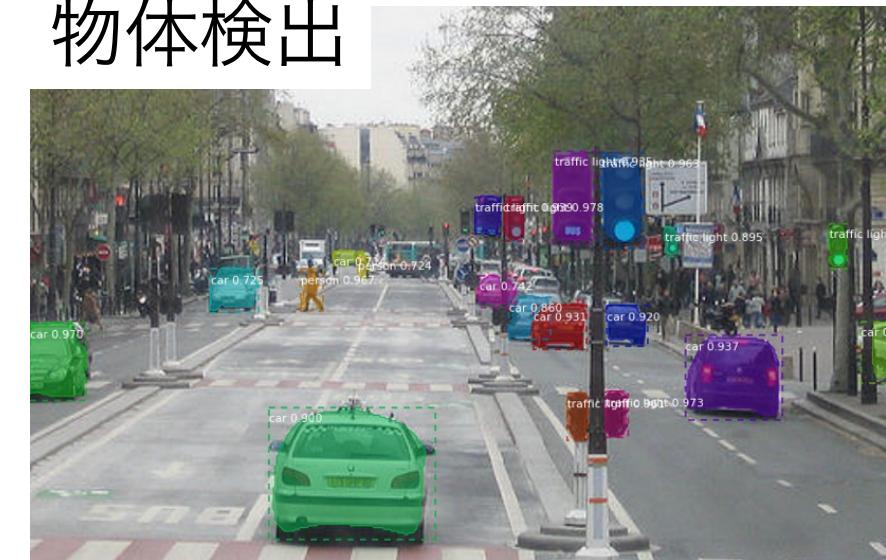


Data size: 140 PB
候補事象: 10^9
～560 年(10人)

分類



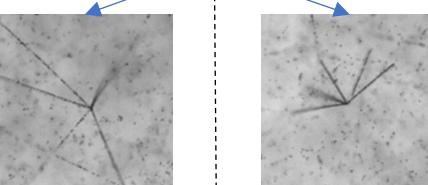
物体検出



Auto pilot
Auto Payment
Security camera
...

適用例

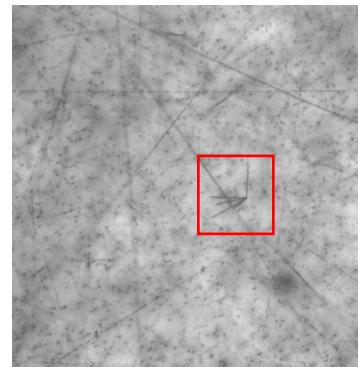
分類タスク



A

B

検出



稀事象に対する訓練データ

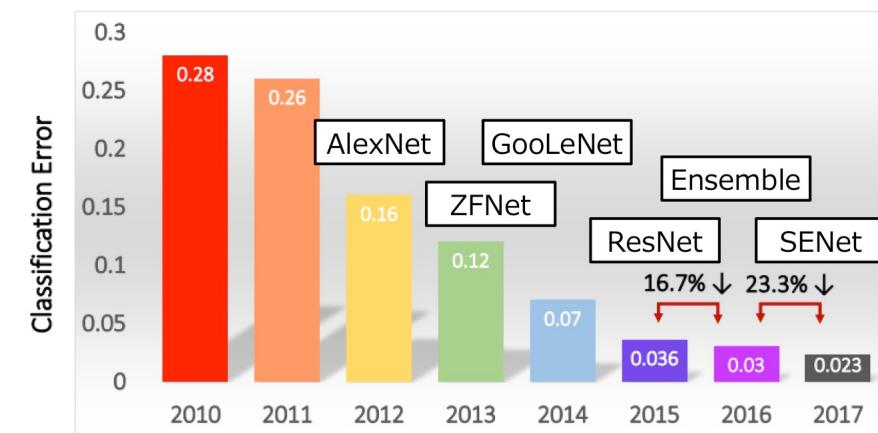
ML + MC simulation

2015: 吉田さん (岐阜大ポスドク) (現在東北大准教授)

「これからは深層学習の時代だ！！」

笠置(B1) 「へえ———(?????)」

2020: 理研・岐阜大・立教などの共同研究がスタート

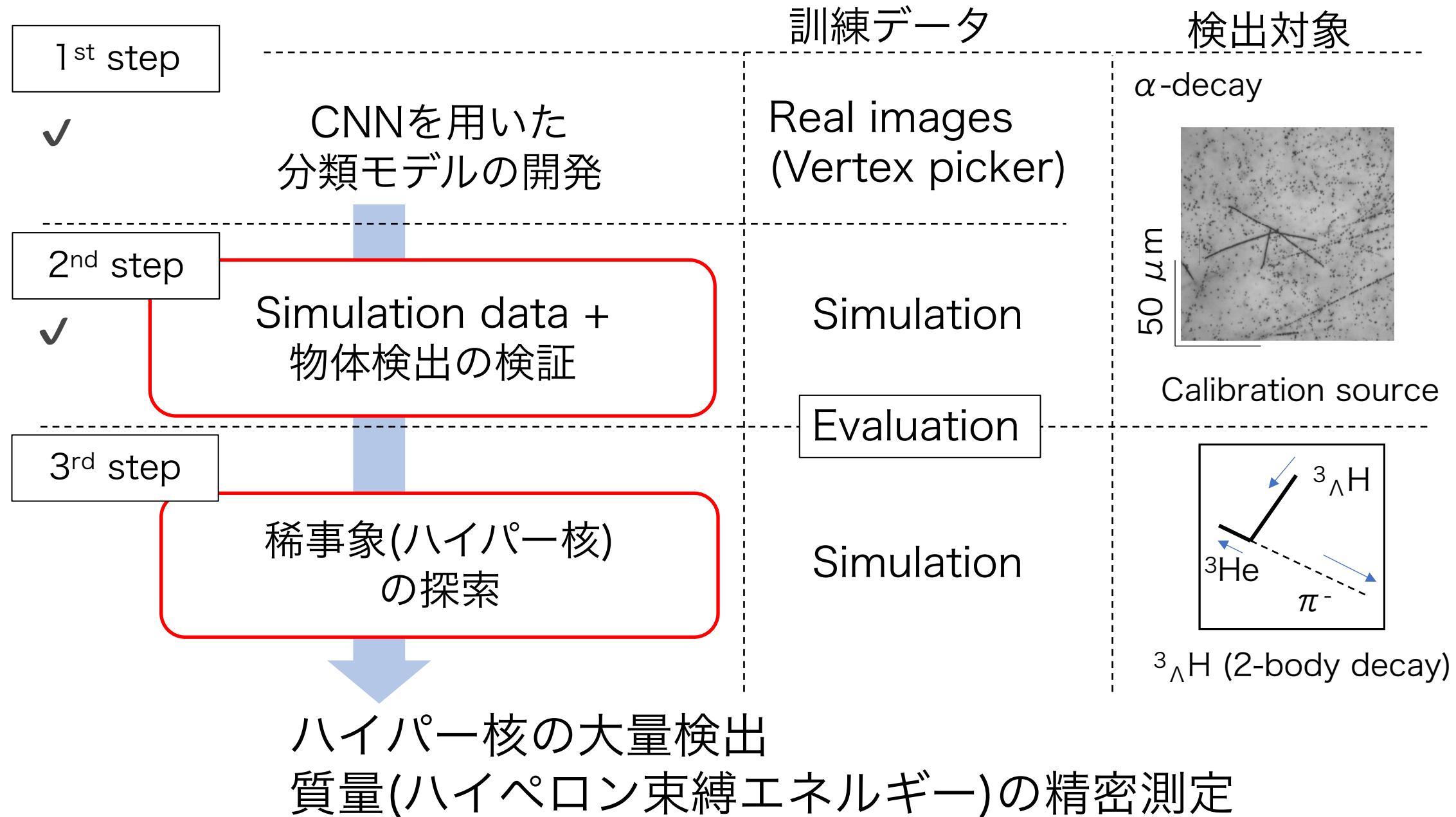


ILSVRC
(Competition of Image classification)
83.5% (2nd 73.8%)

<https://www.kaggle.com/discussions/getting-started/149448>
<https://www.mecs-press.org/ijqsp/ijqsp-v11-n10/IJGSP-V11-N10-5.pdf>
<https://openai.com/chatgpt/>

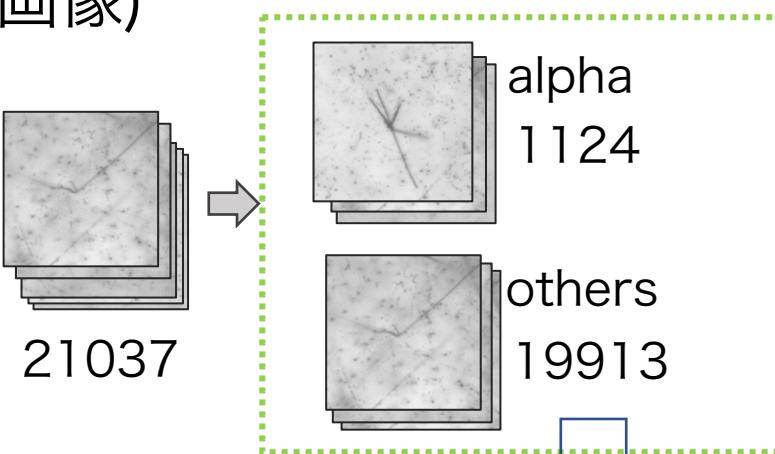
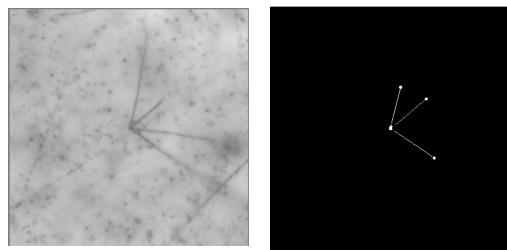


齋藤武彦主任(RIKEN)
瀧雅人准教授(Rikkyo AI)

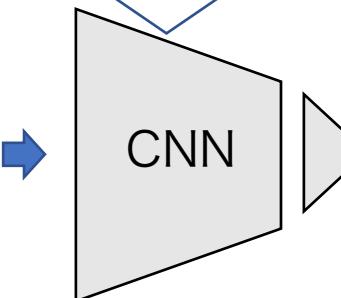


原子核乾板解析に対する深層学習のフィージビリティーは？

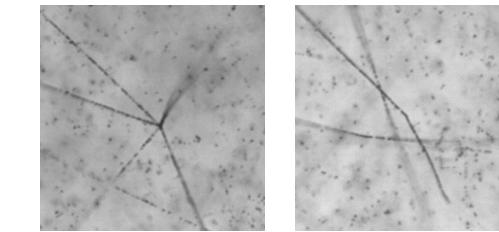
Vertex picker (実画像)



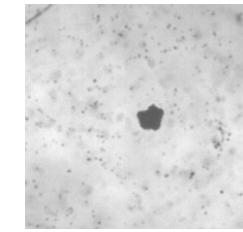
Test data



Noise: others

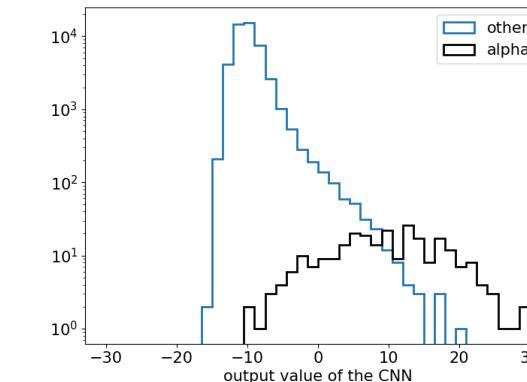
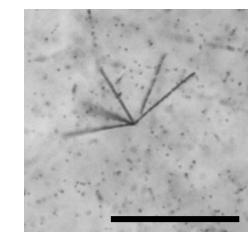


Cross



Dust

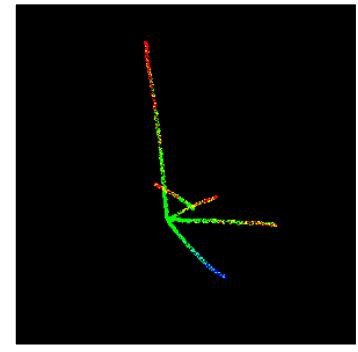
Scalar value

Target: α decay50 μm

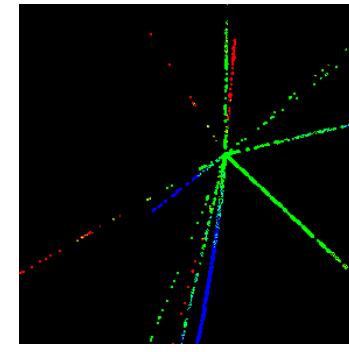
	Purity	Efficiency	No. images
Rule base	0.081 ± 0.006	0.788 ± 0.056	2489
CNN filter	0.547 ± 0.025	0.788	366 ± 18

実データがない稀事象への訓練データを生成

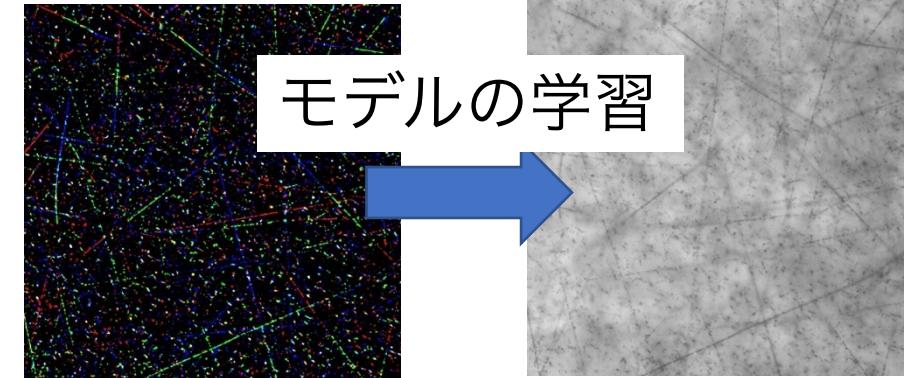
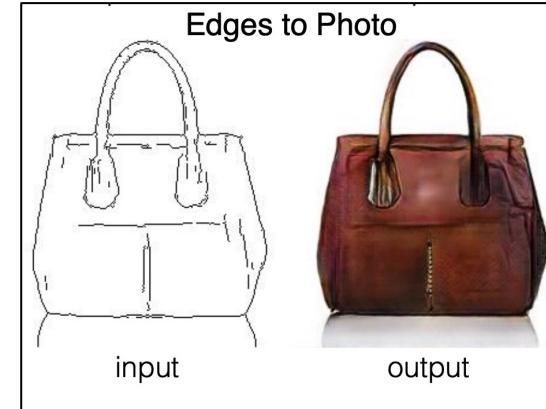
α 崩壊事象



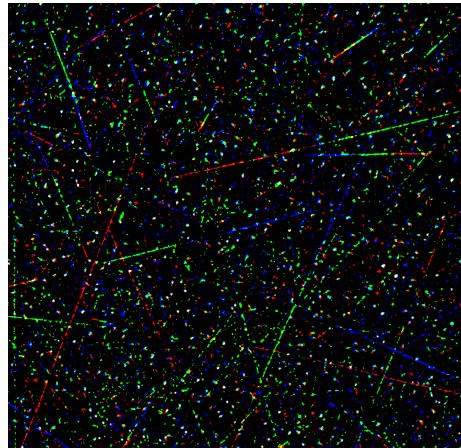
核破碎反応



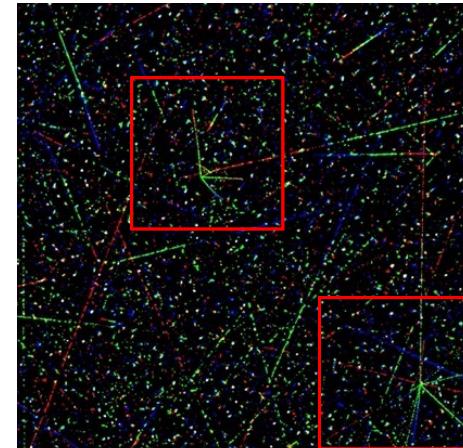
GAN: pix2pix(画風変換機械学習モデル)



背景画像
(実画像を処理)

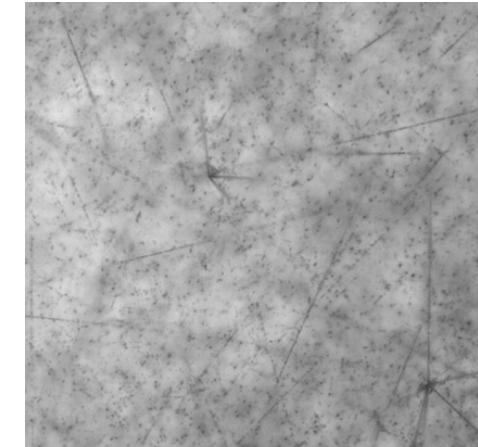


全て合成



学習済みモデルで変換

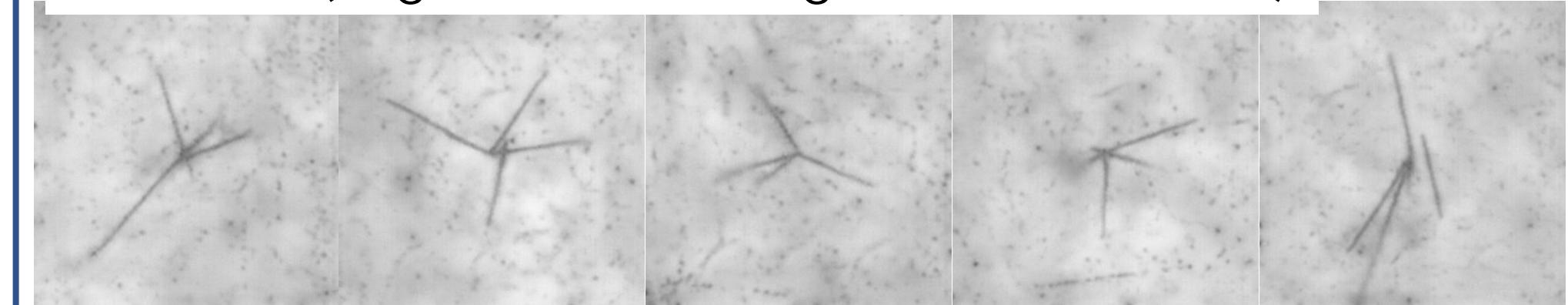
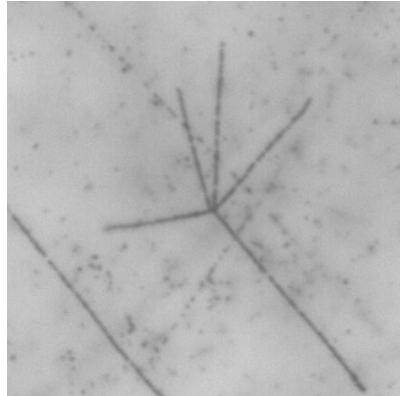
シミュレーション画像



<https://arxiv.org/abs/1711.07004>

pix2pixで作った大量の画像CNNを訓練してみたが…

Real Simulated (huge size of training data 20k → 100k)

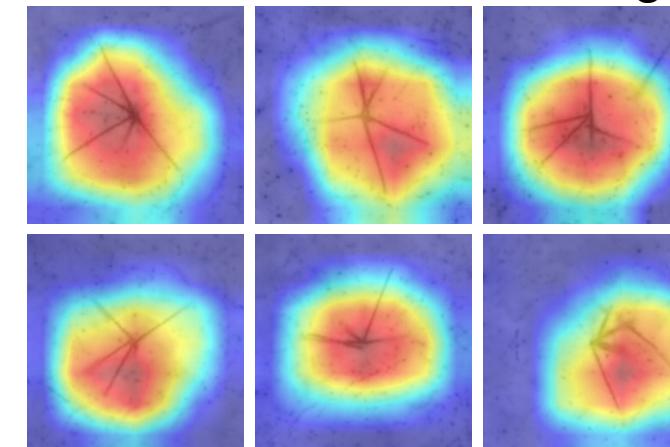


Training data	Efficiency [%]
Real	~79%
Simulated	~30%

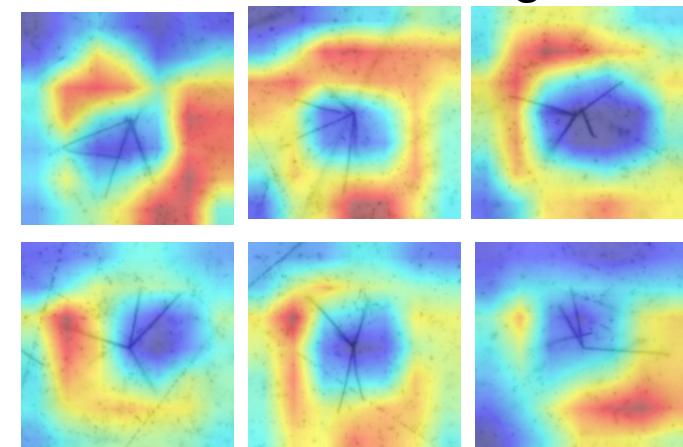
- ・モデル変更: → pix2pixHD
- ・タスクの変更:
分類 → 物体検出

Grad-CAM: <https://arxiv.org/abs/1610.02391>

Results for Simulated images

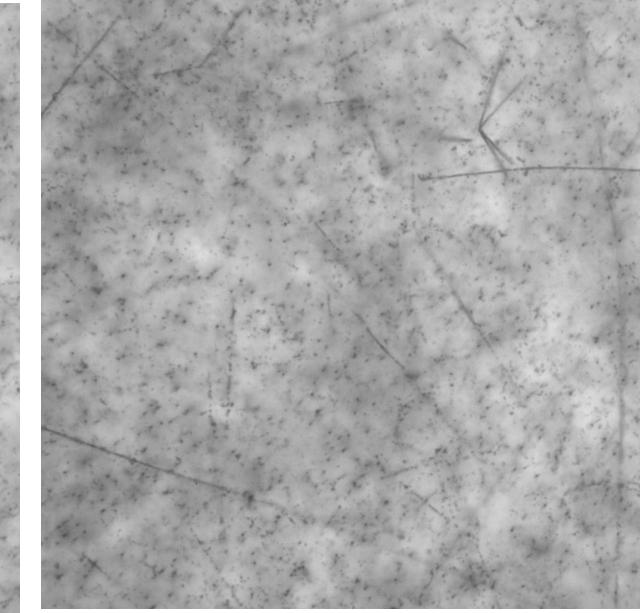
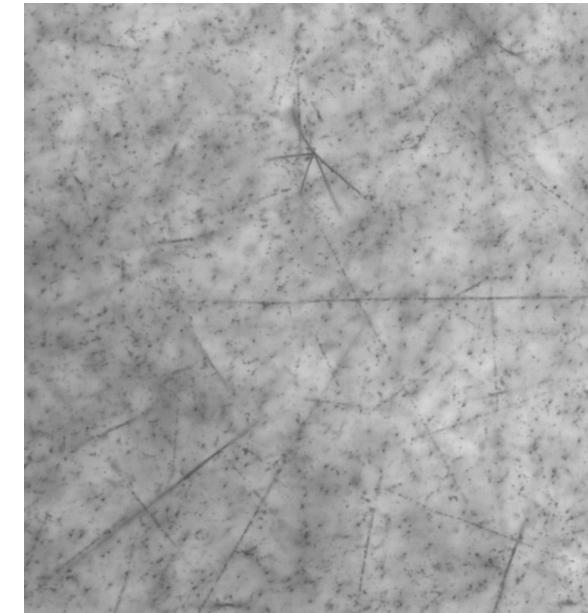
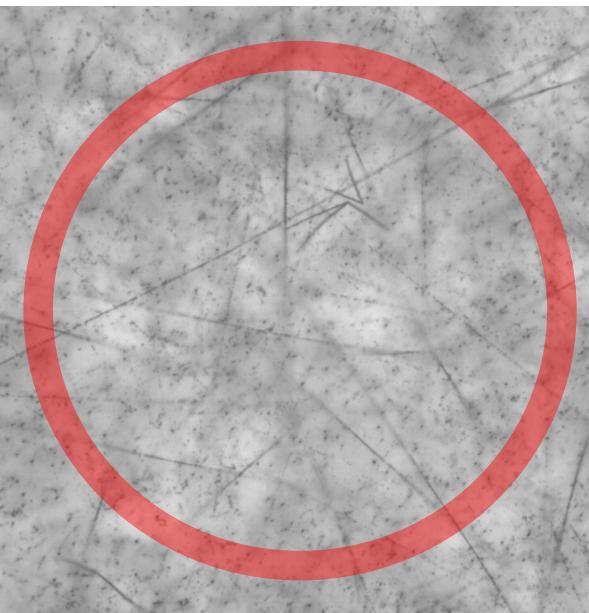
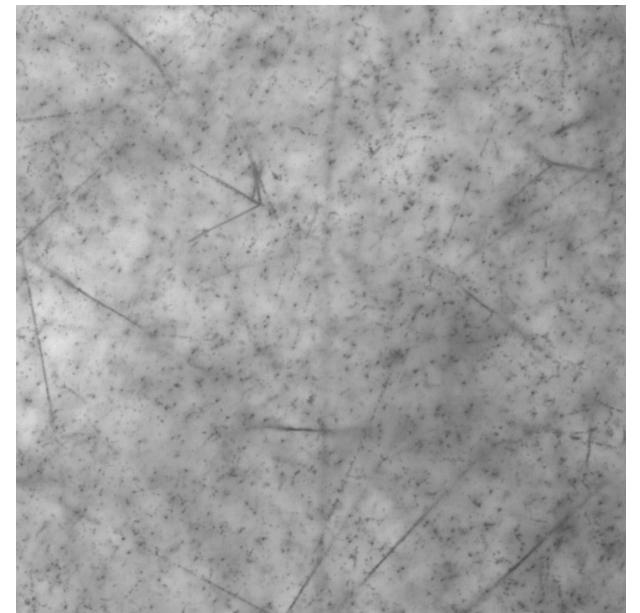
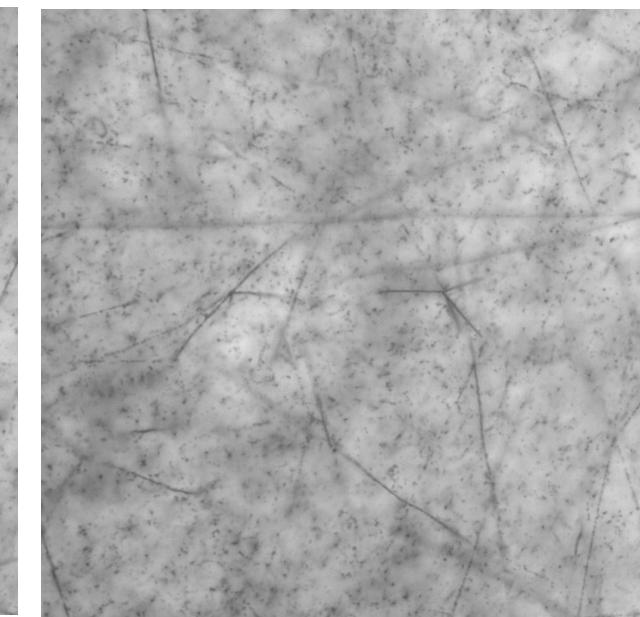
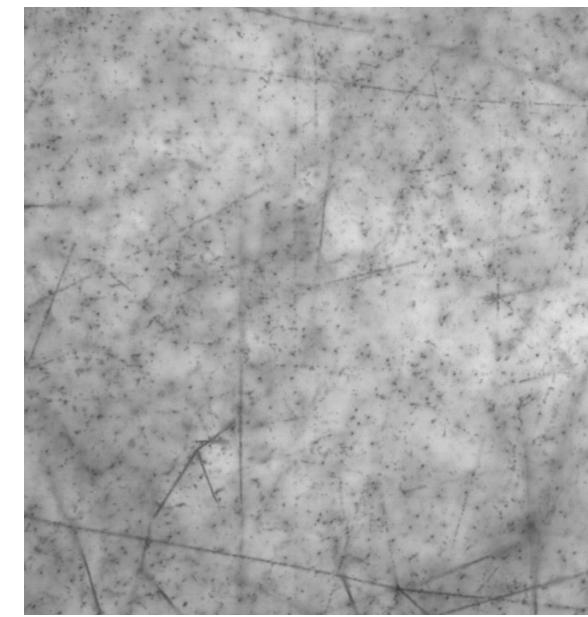
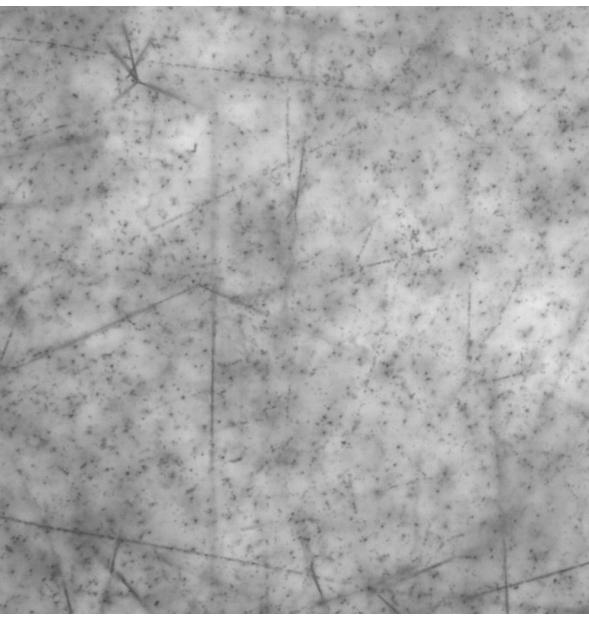
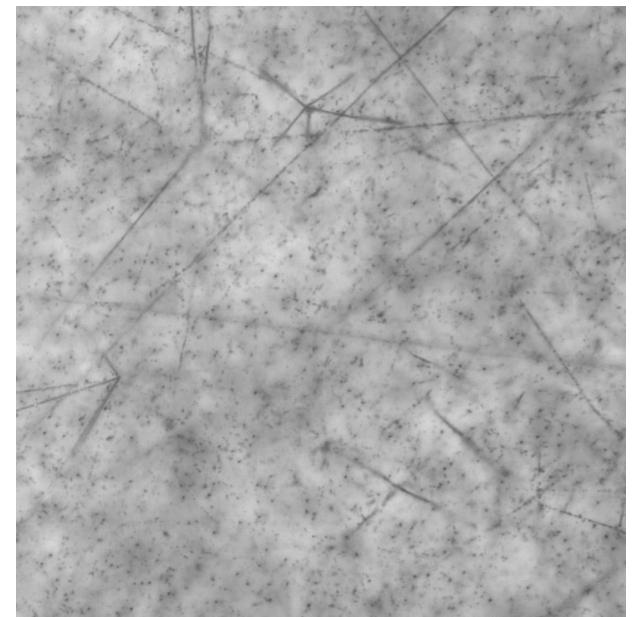


Results for Real images

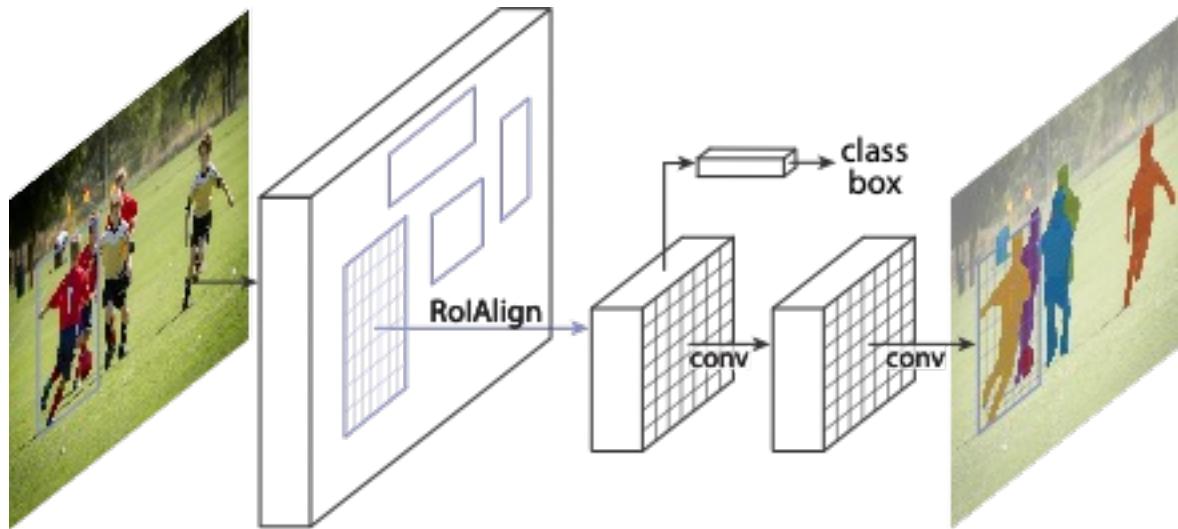


画像生成改善後: ど�が本物?

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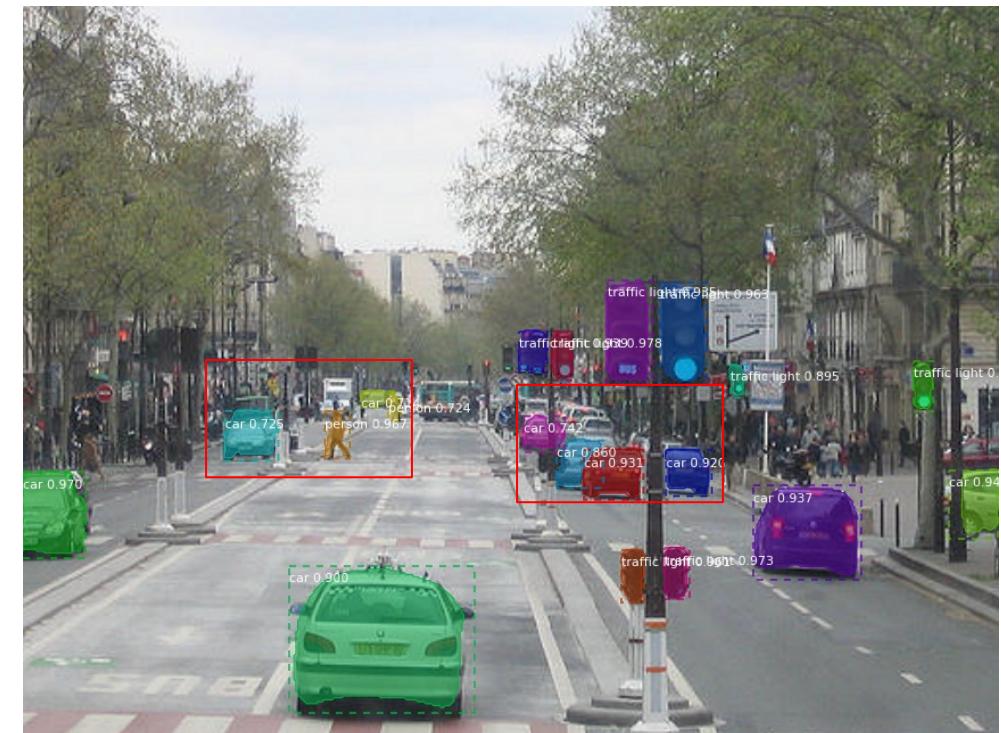
検出対象の位置・形・ラベルの識別



<https://arxiv.org/abs/1703.06870>

https://github.com/matterport/Mask_RCNN

- 直接検出
- 分類Score: (0~1)
- Segmentation -> 飛跡解析



分類Score

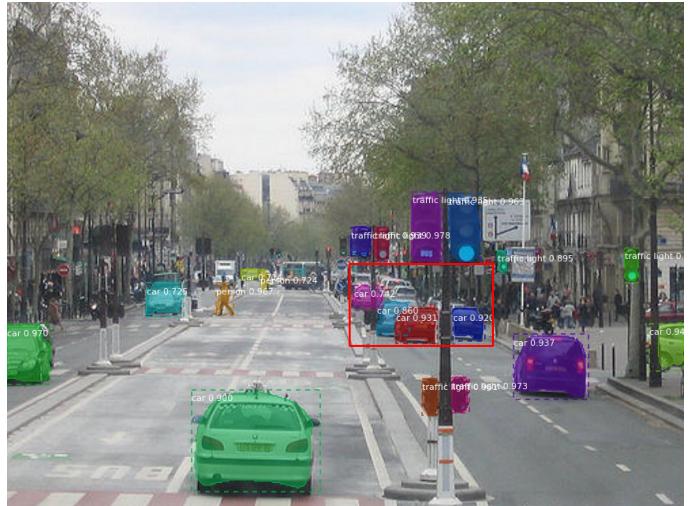


混み合った場所でも

Simulation画像による物体検出モデルの訓練

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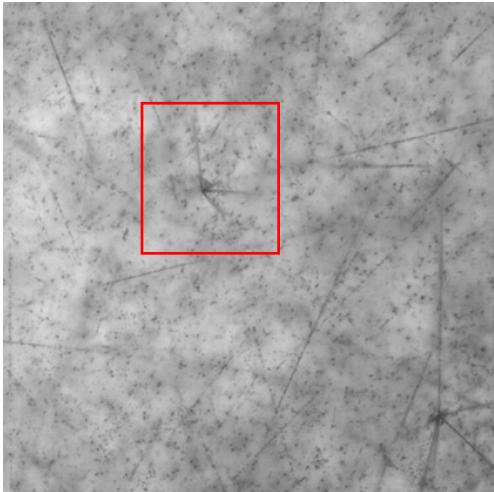
Mask R-CNN



訓練データの例



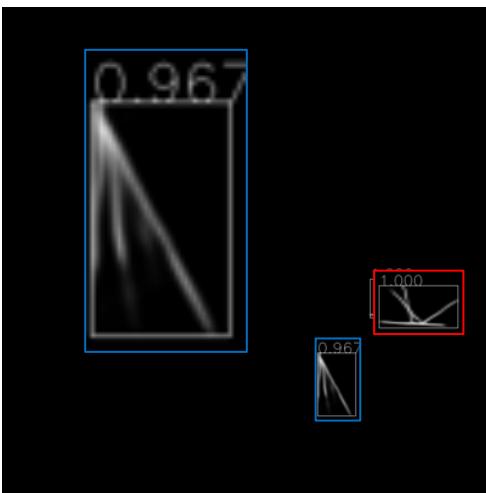
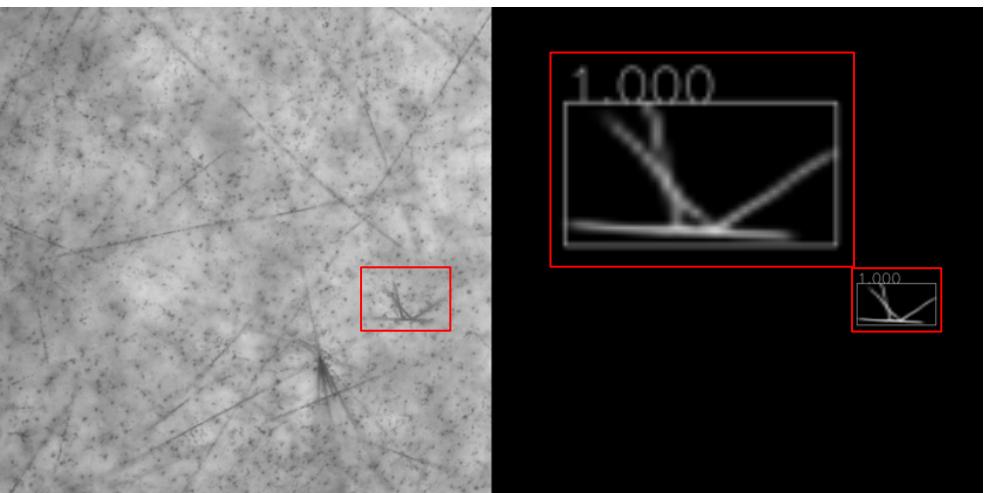
Training data (Simulation)



テスト画像(Simulation)への適用

50 μm

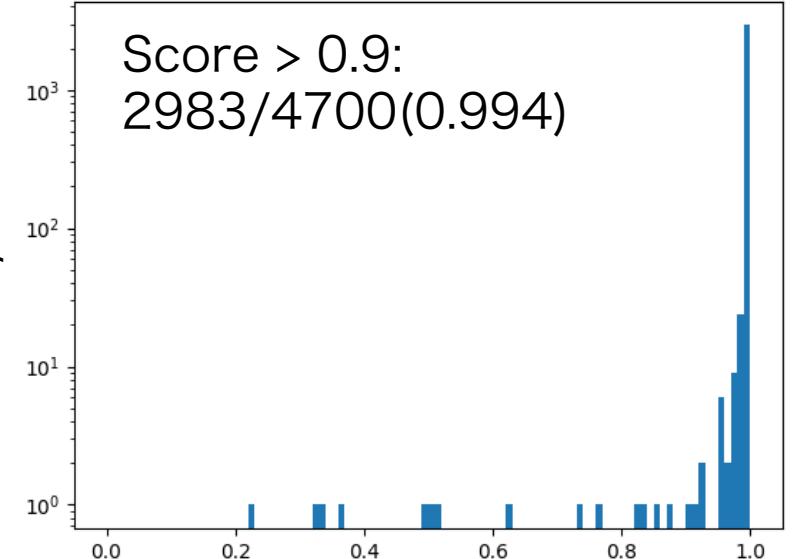
アノテーション不要



wo/ negative sample

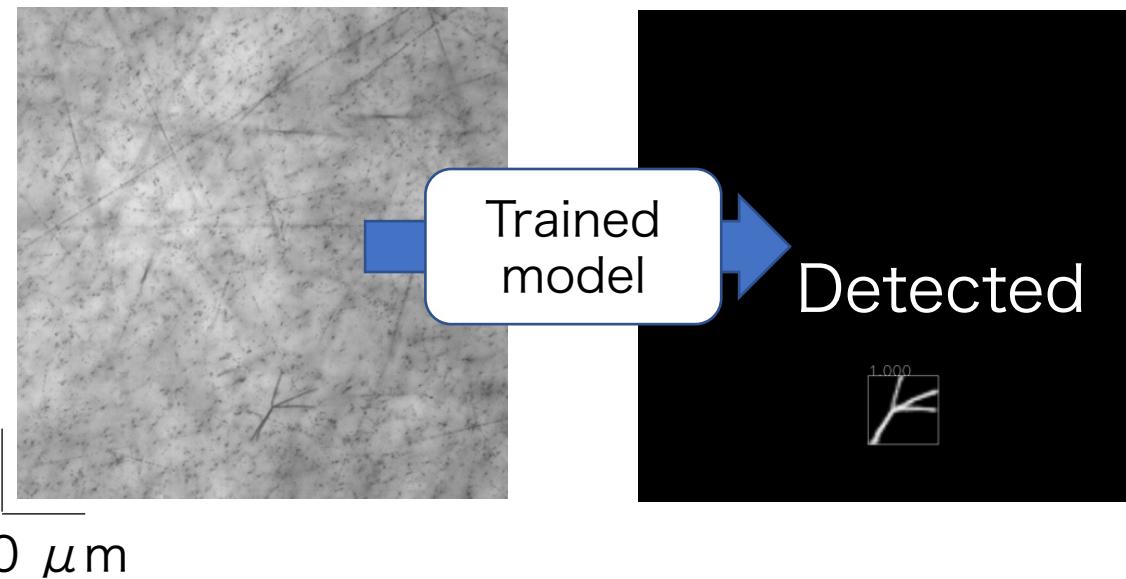
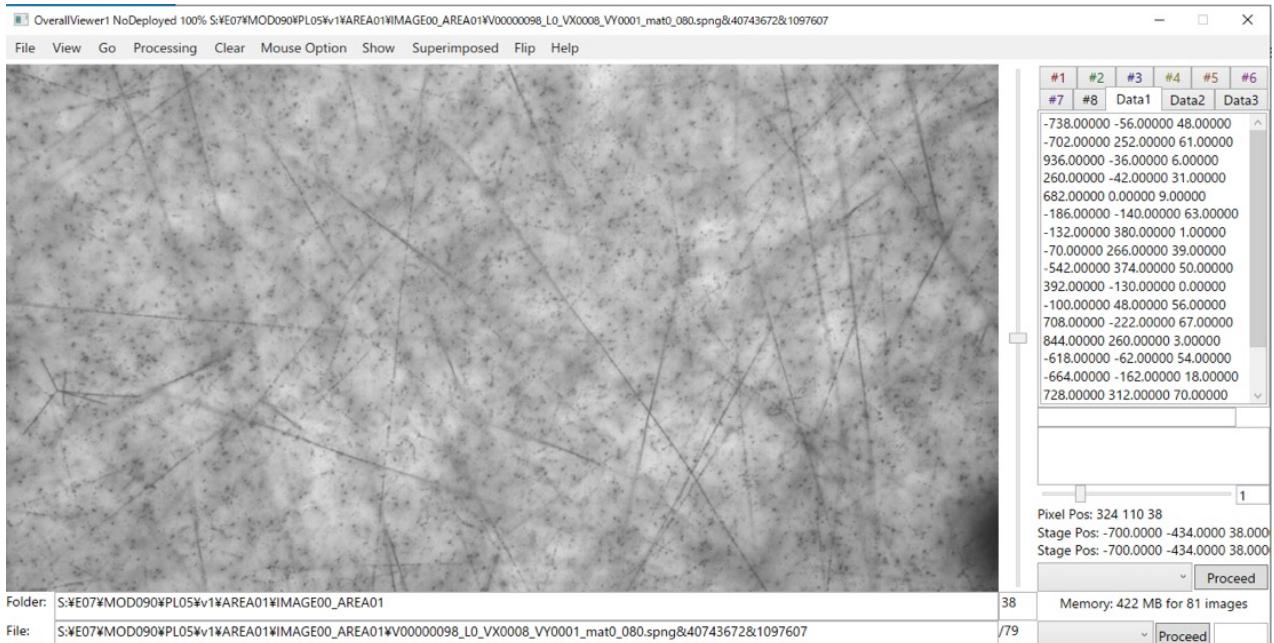
Counts/0.01

Score > 0.9:
2983/4700(0.994)



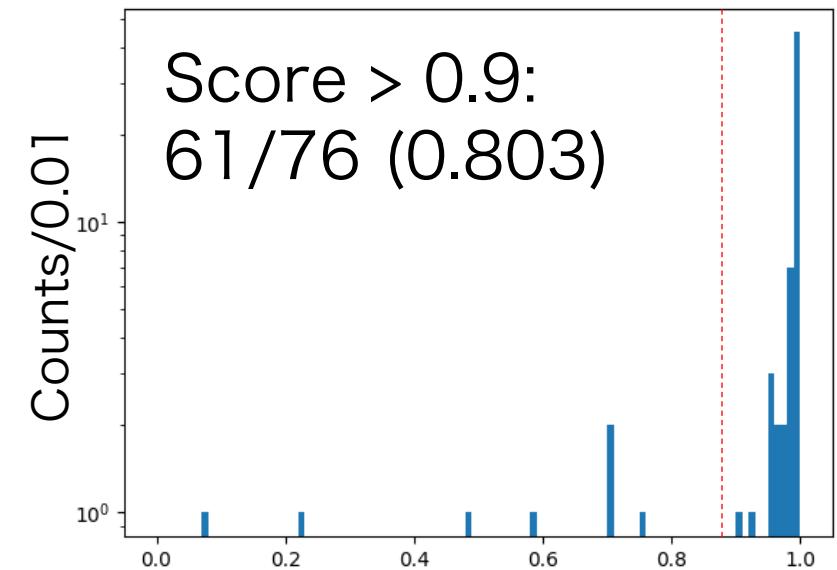
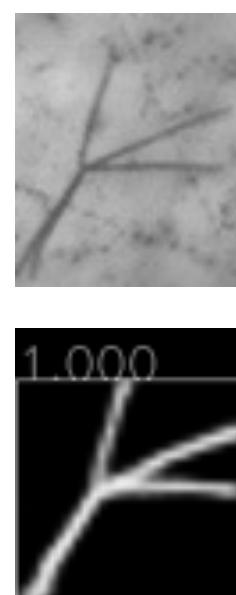
α 崩壊事象実データを用いた性能評価

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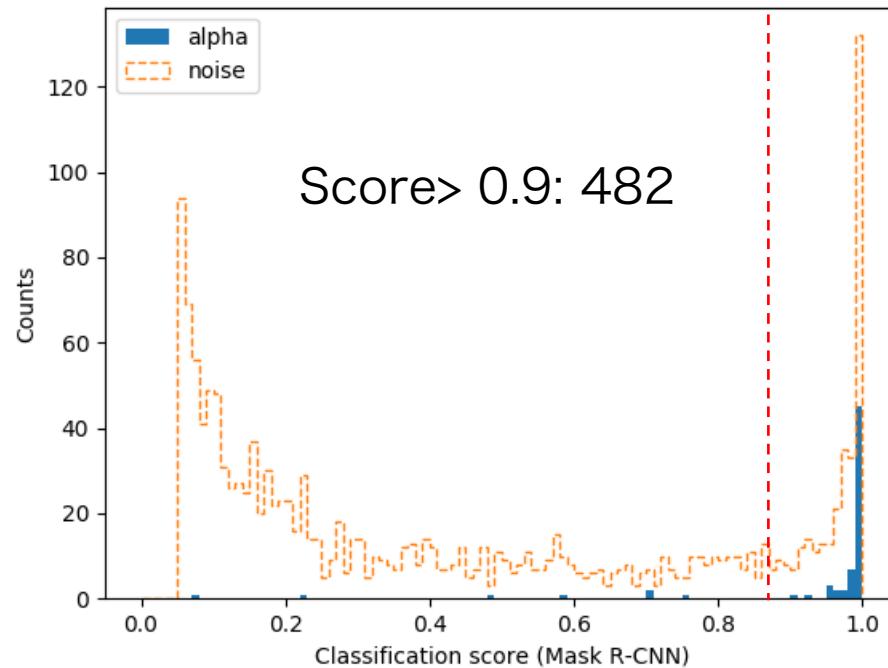
- 120k画像(1.8 cm^2)を目視
(100時間以上)
→ 76 α -decay event

Efficacy: Y/76、 Purity: Y/X

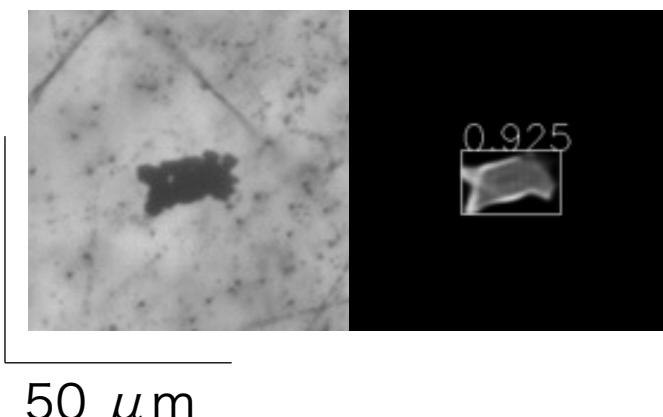


実データにも汎化

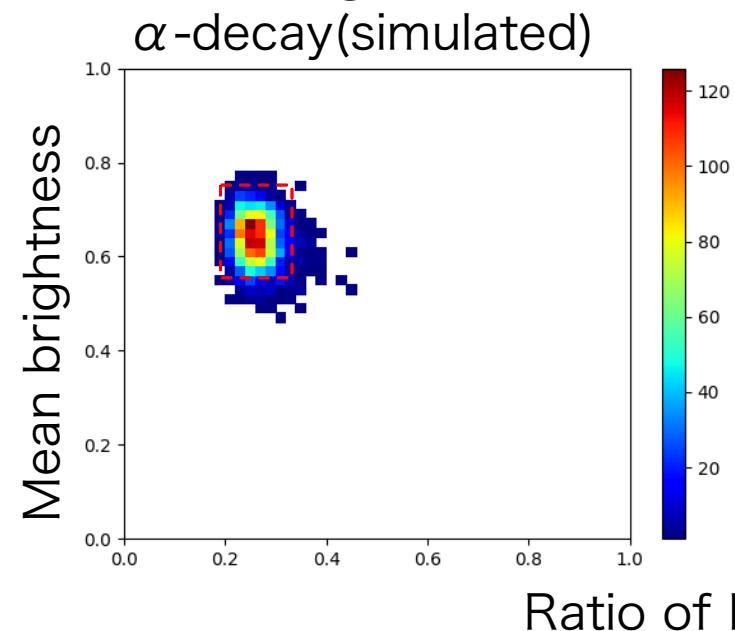
Score distribution



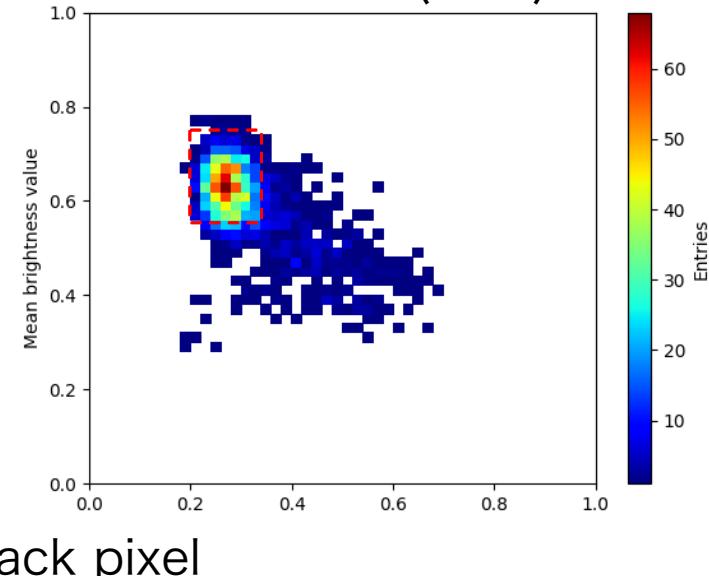
現像で紛れ込むDust



Segmentation結果を活用した解析

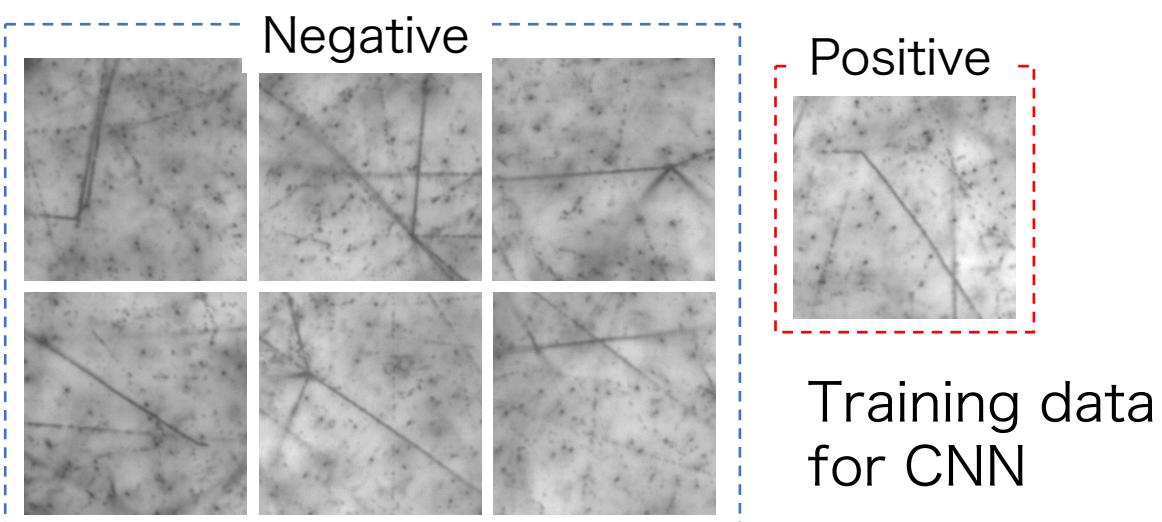
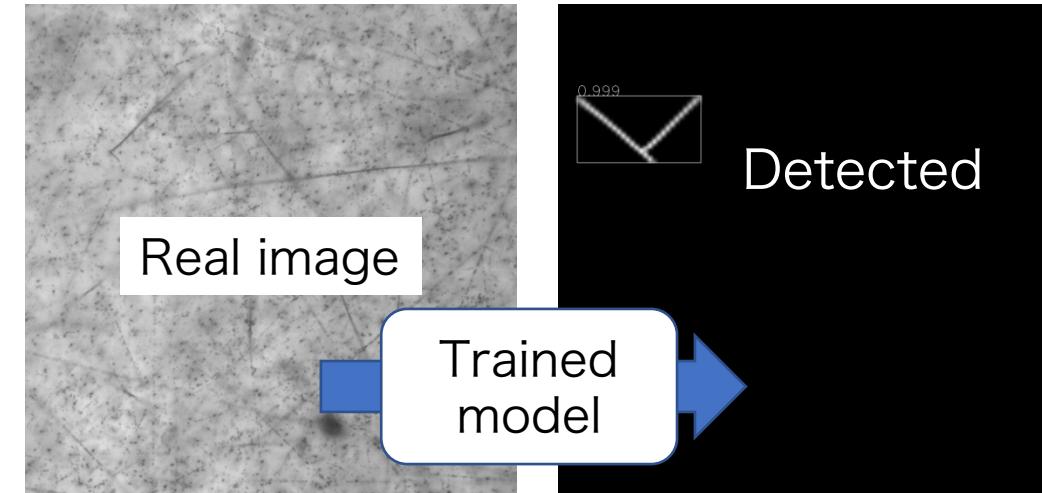
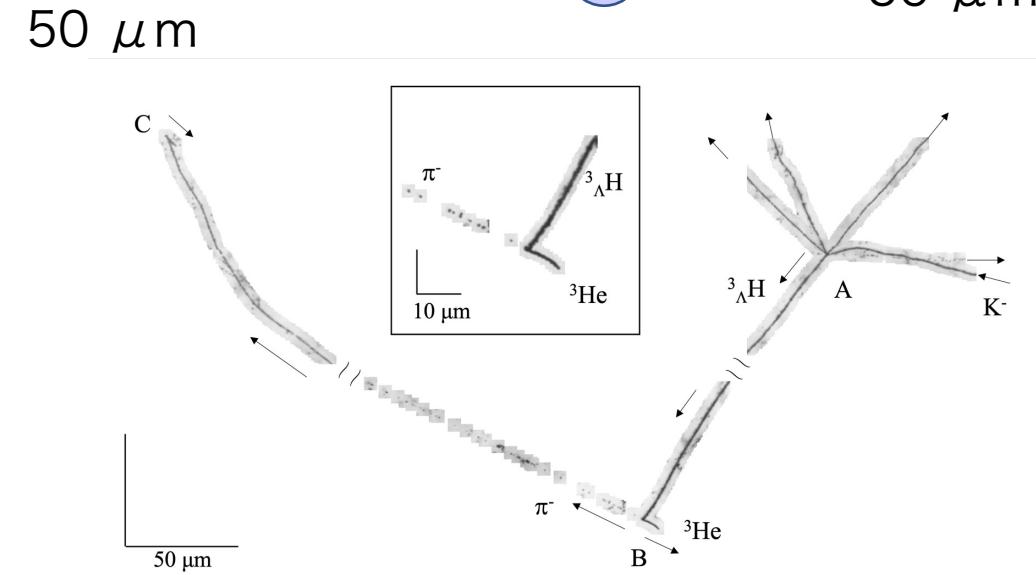
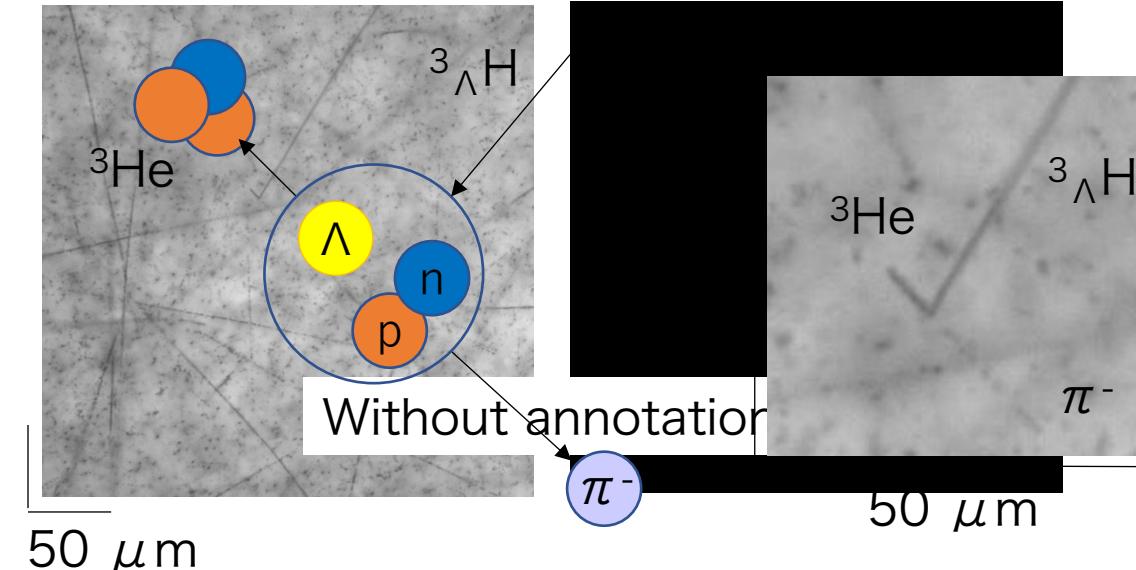


Candidates (Real)



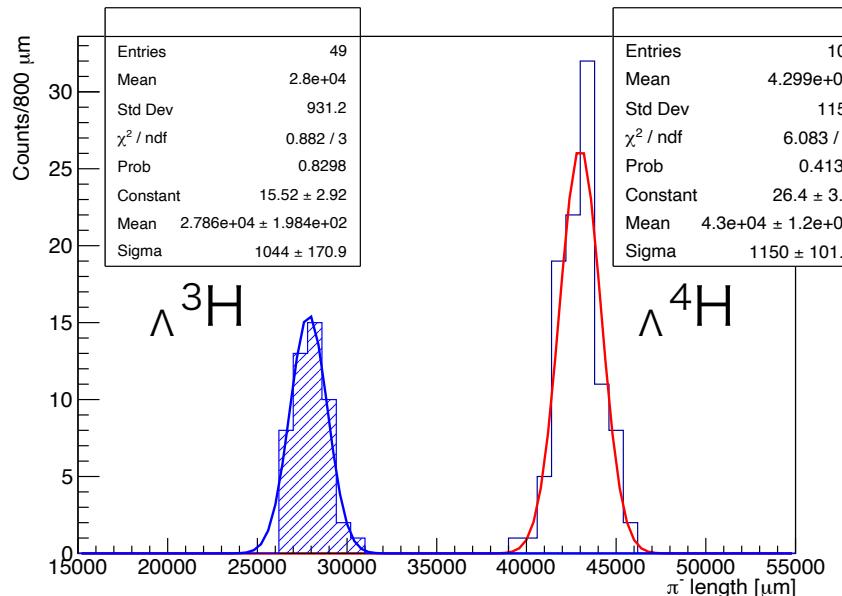
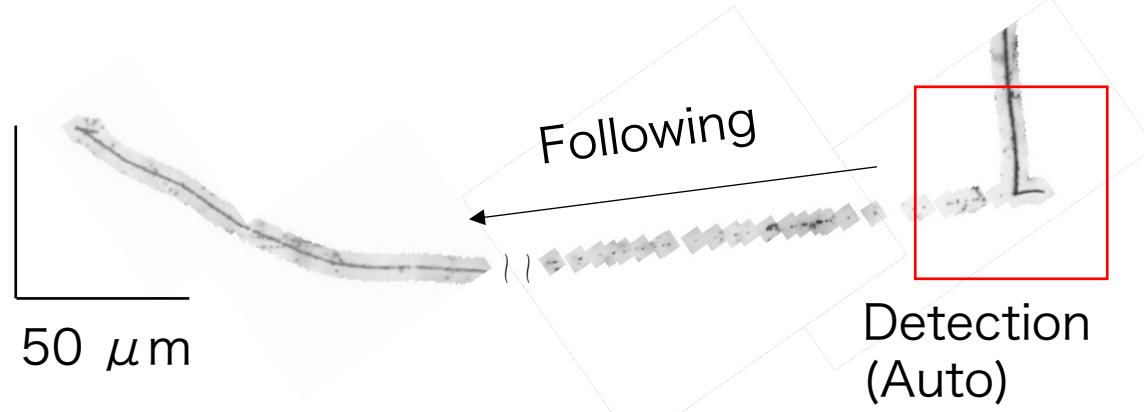
	Cand.	Detect	Efficency [%]	Purity [%]
VP	3105	31/76	$40.8^{+5.6}_{-5.5}$	~ 1.0
VP + CNN	1347	31/76	$40.8^{+5.6}_{-5.6}$	~ 8.9
Mask R-CNN	482	61/76	$80.3^{+4.2}_{-4.8}$	~ 12.6
Dust reduction	352	61/76	$80.3^{+4.2}_{-4.8}$	~ 17.3

Simulationデータのみでモデルを訓練し稀事象を探索

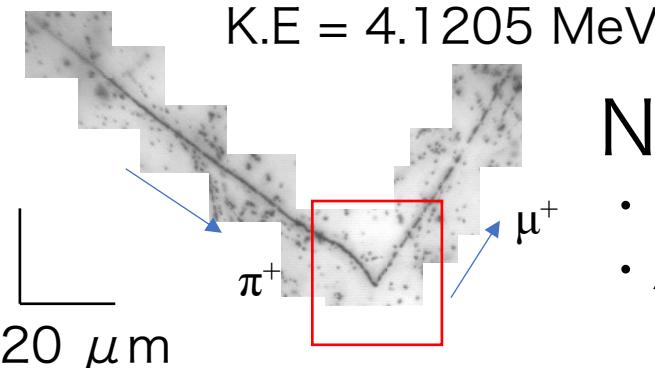


目視量: 1/10⁴・稀事象検出手法を確立

深層学習による自動検出 + 事象ごとの個別解析

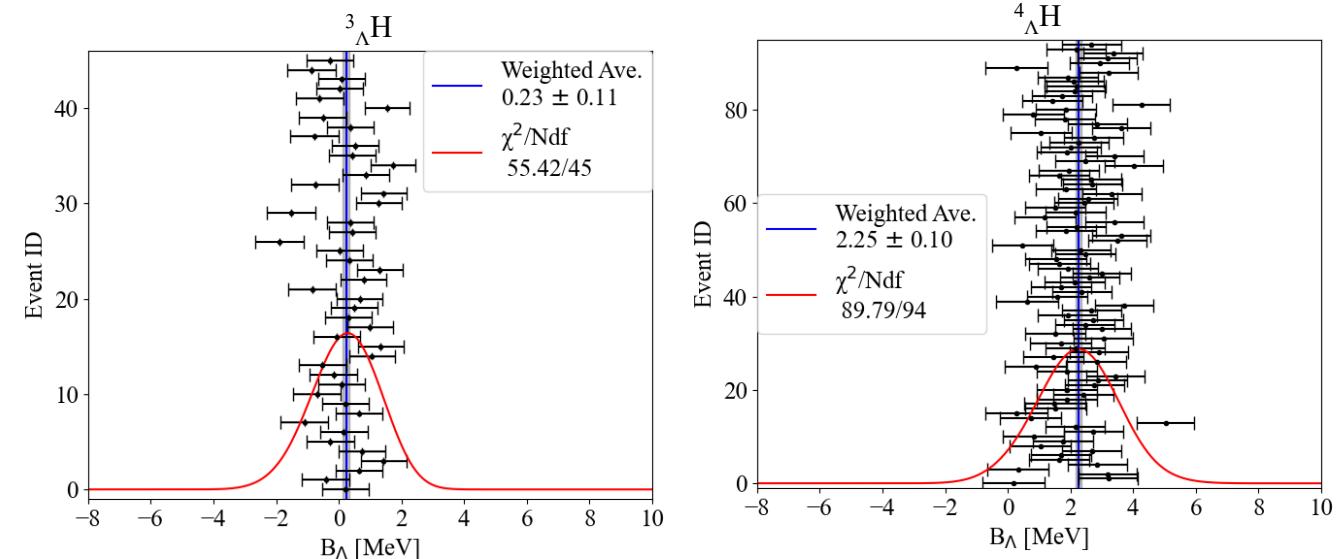


$\Lambda^3\text{H}$: 49, $\Lambda^4\text{H}$: 101 (from 0.6%)



New calibration

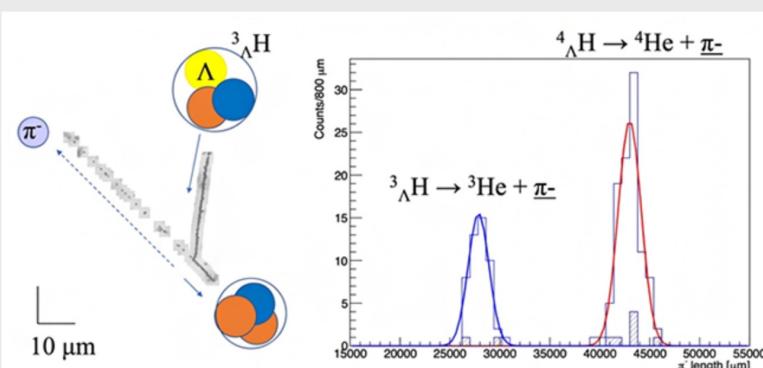
- $\pi^+ \rightarrow \underline{\mu^+} + \nu_\mu$
- ATIMA (GSI)



同じデータ解析から
2種のハイパー核質量を算出

深層学習×写真フィルムでハイパー核の質量を測定

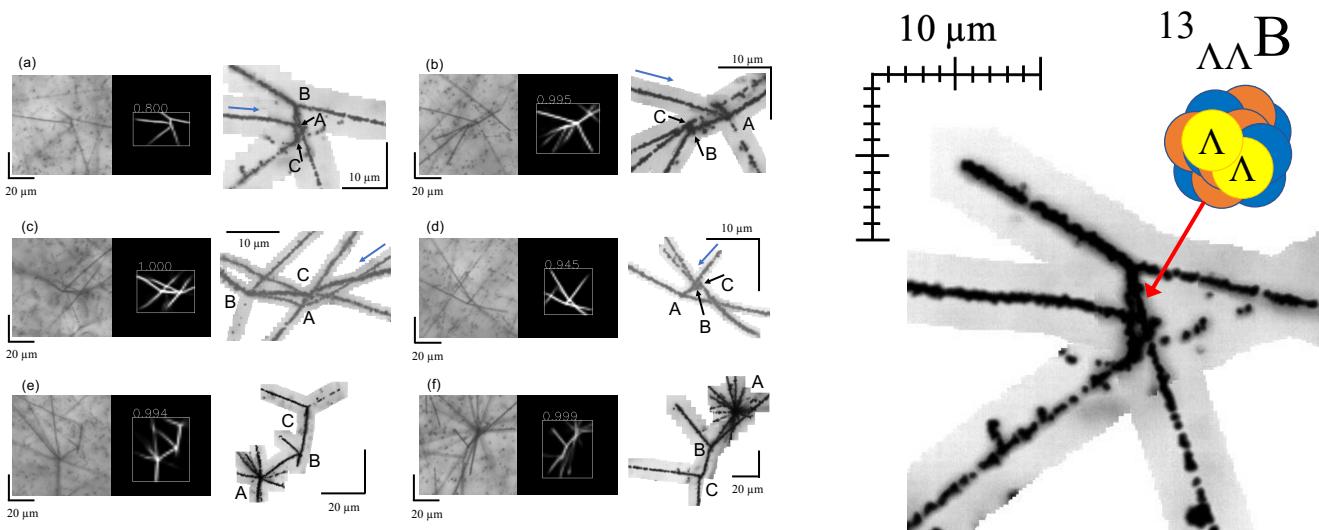
ノイズを排除した解析手法で新たな結果を取得



深層学習で検出したハイパー核の2体崩壊事象と飛程による同定解析の結果

Article in Press

Artificial intelligence pioneers the double-strangeness factory

<https://doi.org/10.1038/s41467-025-66517-x>

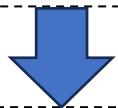
Double- Λ 核の一意な同定(史上2例目)

原子核乾板 + 深層学習のポテンシャルを実証
→ 高速化効率化による大量検出へ

高速・Robustな多種多様のハイパー核事象検出へ

顕微鏡による画像取得

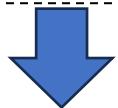
- ・ピエゾ素子を用いた高速読み取り ✓



Acknowledgments to Dr. Yoshimoto & F.Lab

画像→Hit情報へ

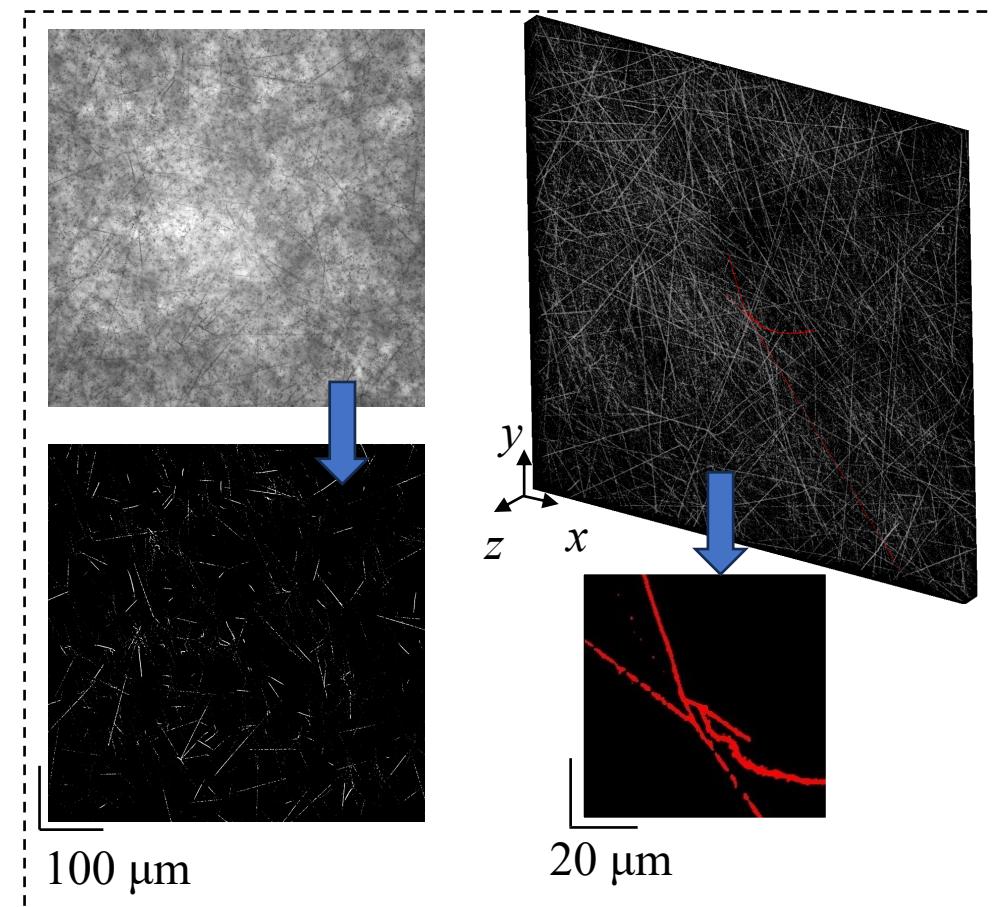
- ・Segmentationタスクの流用
 - Hit抽出に特化した軽量モデルの開発 ✓



飛跡・事象の3D再構成

- ・複雑な構造の検出と解析
 - 3体崩壊・ダブルストレンジネス核

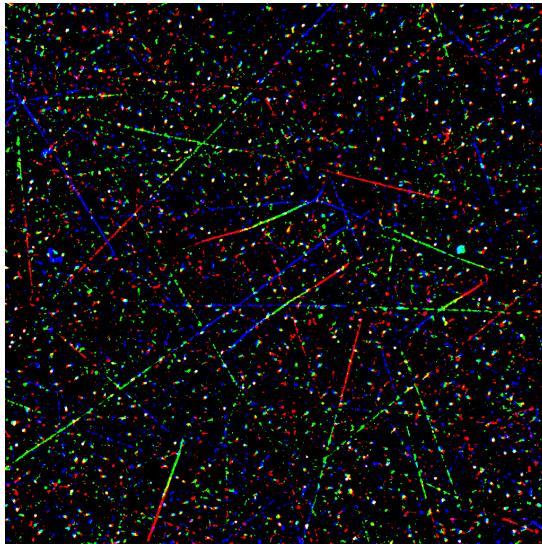
岐阜大学横田氏・仲澤氏らとの共同研究



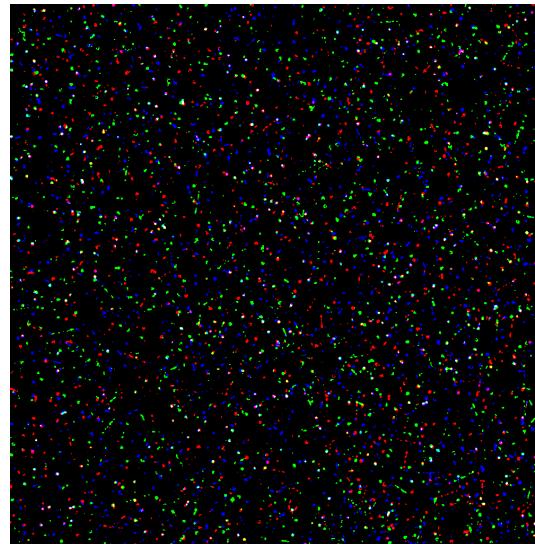
新しい訓練データの生成

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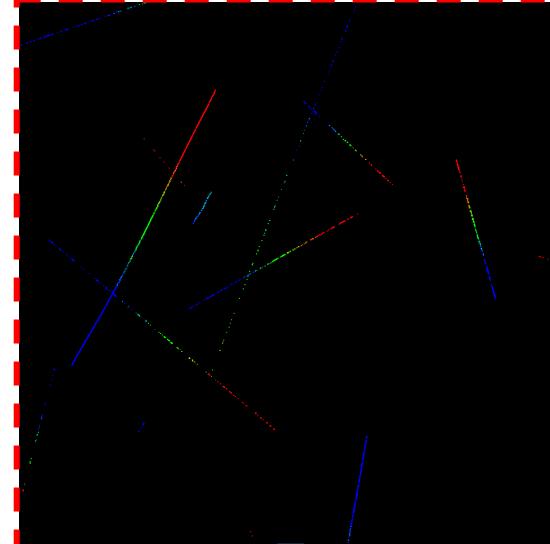
Background(Real)



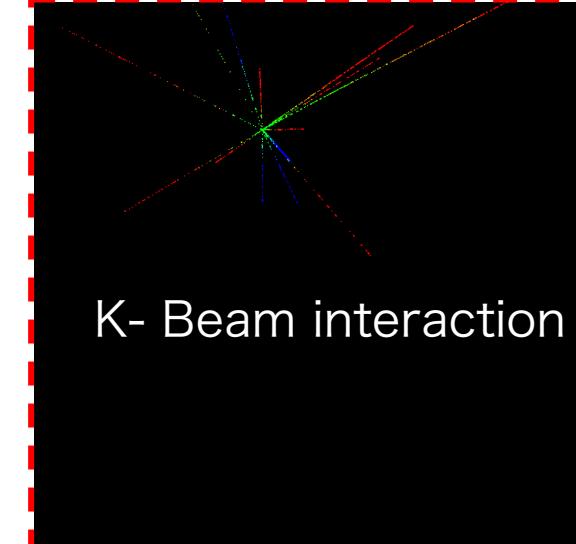
fog & beam(toy MC)



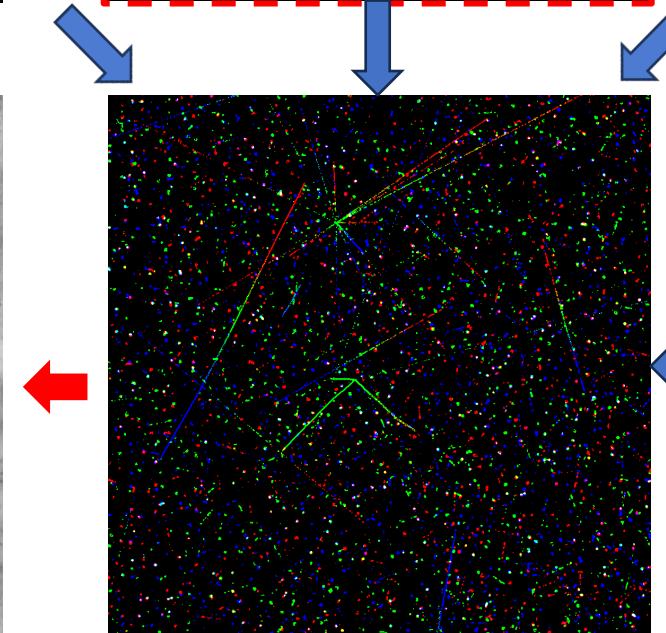
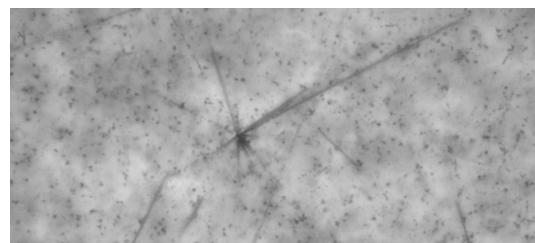
Unrelated tracks(Geant4)



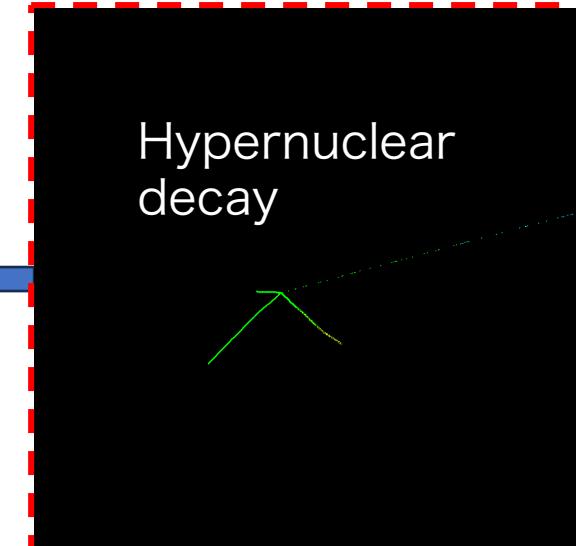
Physics process(Geant4)



全ての飛跡情報を保持し
顕微鏡風画像を生成



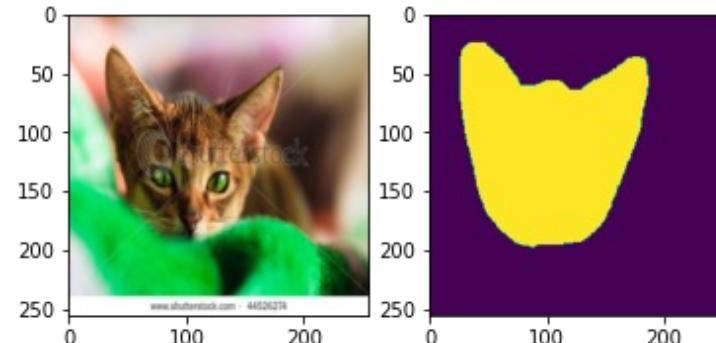
Hypernuclear
decay



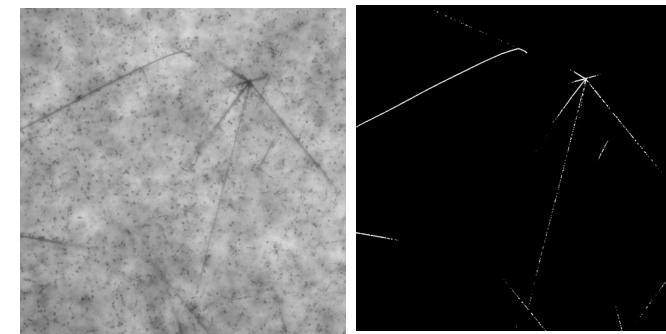
SegmentationによるHit情報の抽出

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軽量Binary Segmentationモデルを訓練
40k枚の画像 + Full scratch



Raw data

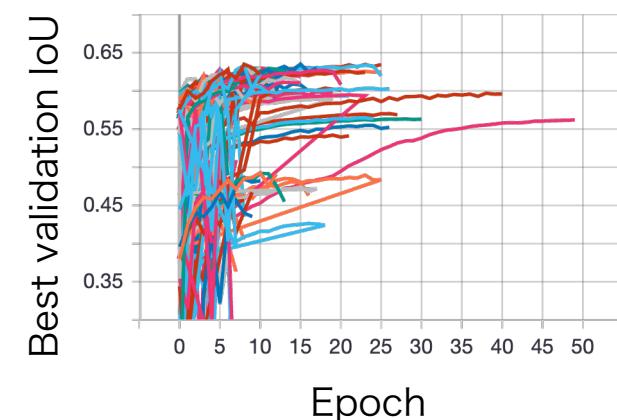


Conventional



Present work

Optunaによるハイパラサーチ



IoU	0.659
F1_score	0.795
Accuracy	0.998
Precision	0.748
Recall	0.805

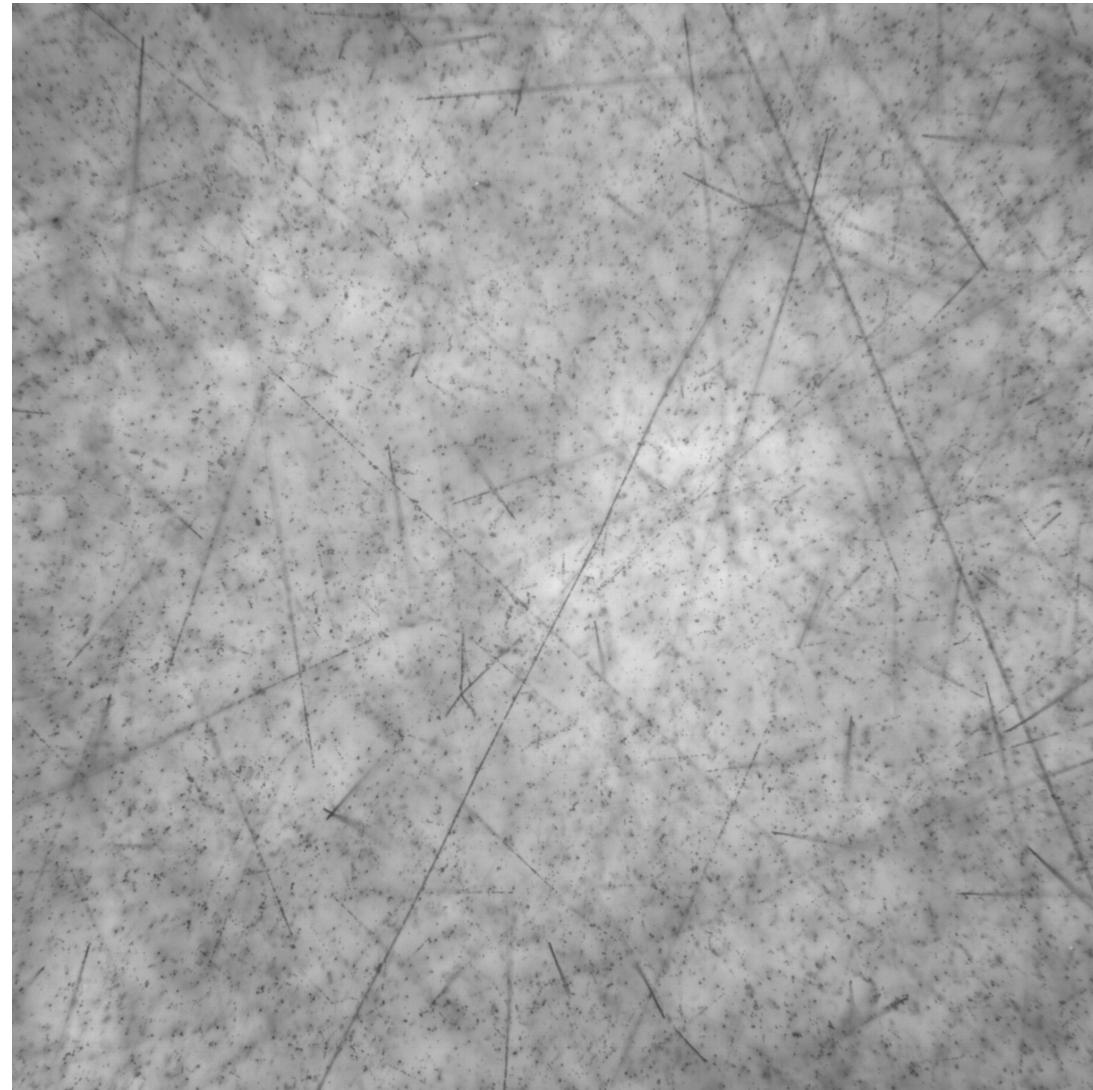
- ・背景除去
- ・Datasize: 1/200

E07 image data
140 PB → 750 TB

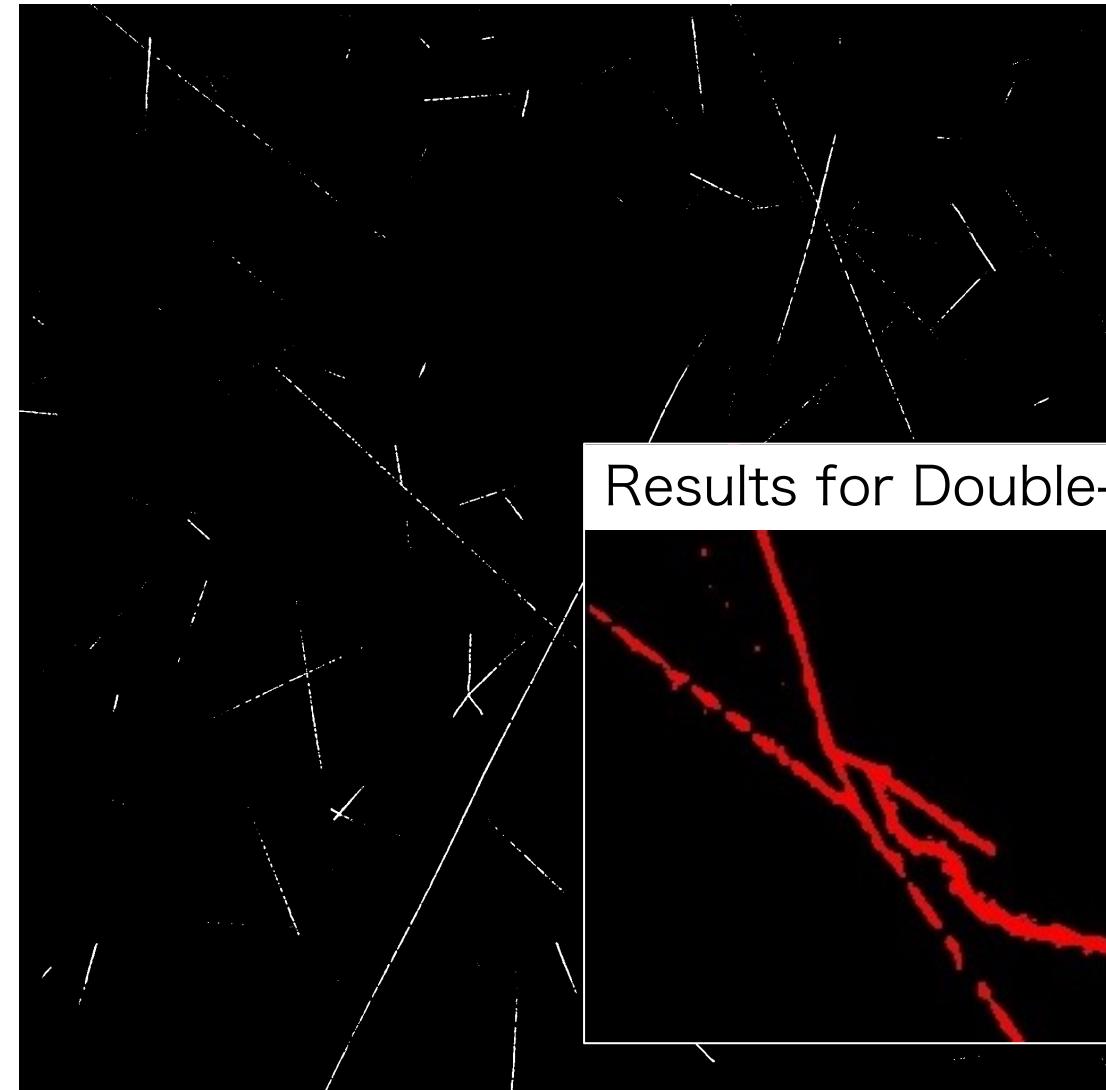
SegmentationによるHit情報の抽出

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Raw data: 200 MB

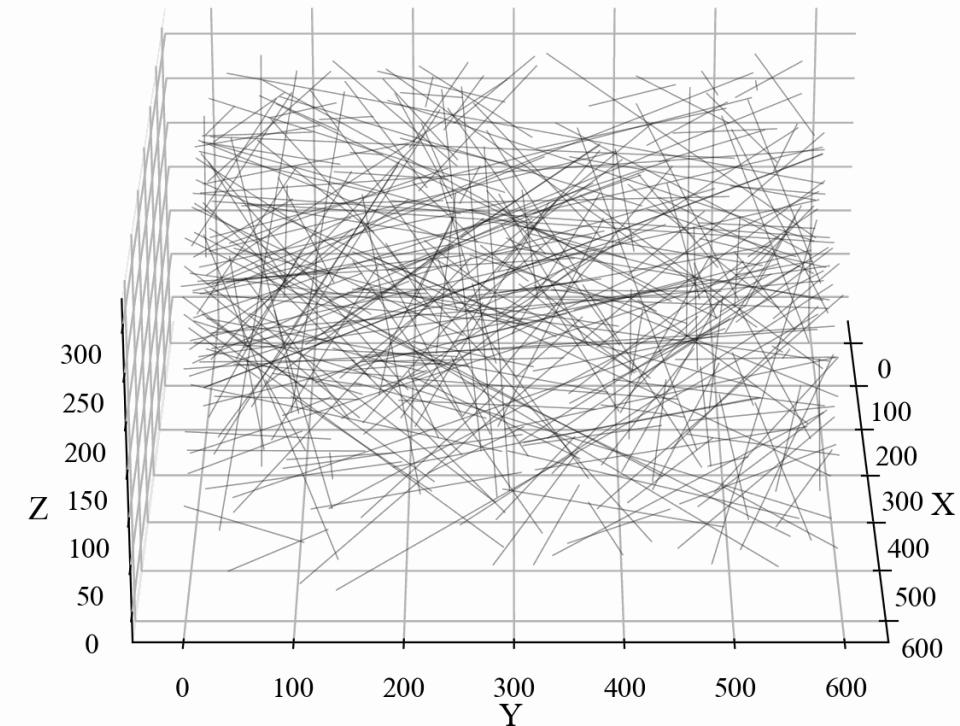
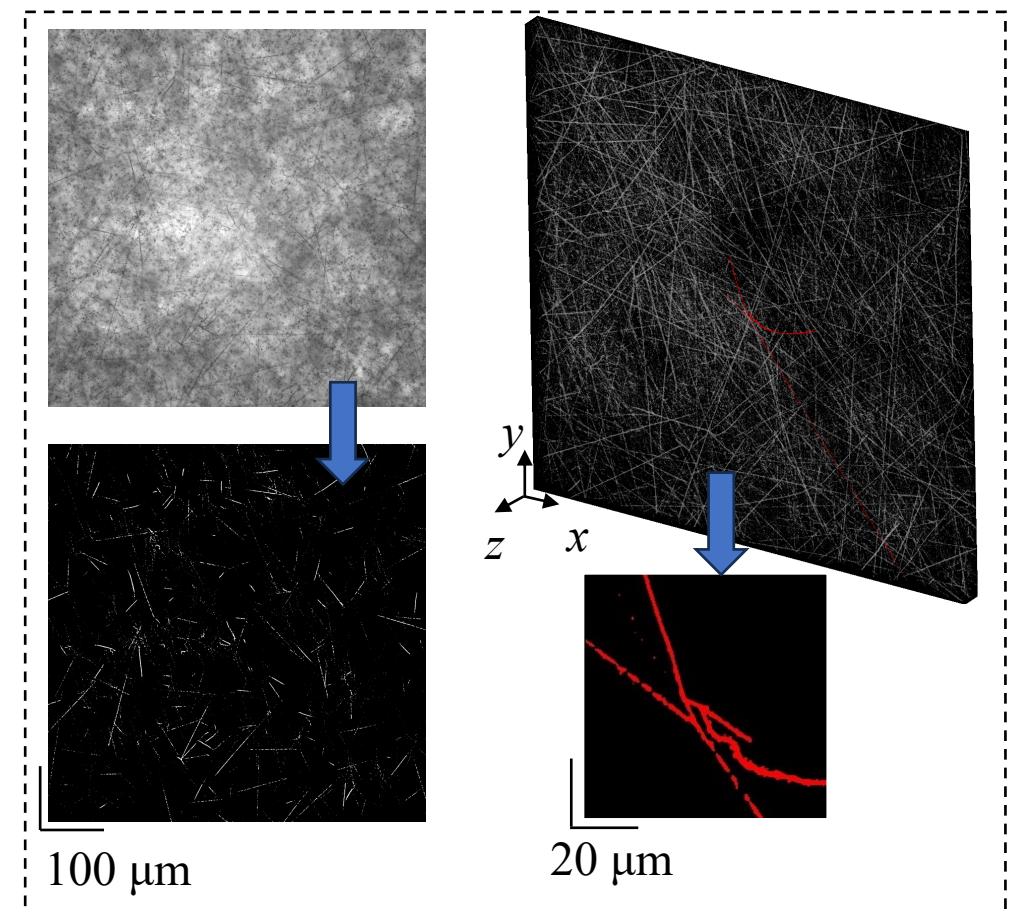


Segmentation: 1MB



100 μm

画像情報から飛跡抽出 → 軽量で多種のハイパー核に汎用な解析へ

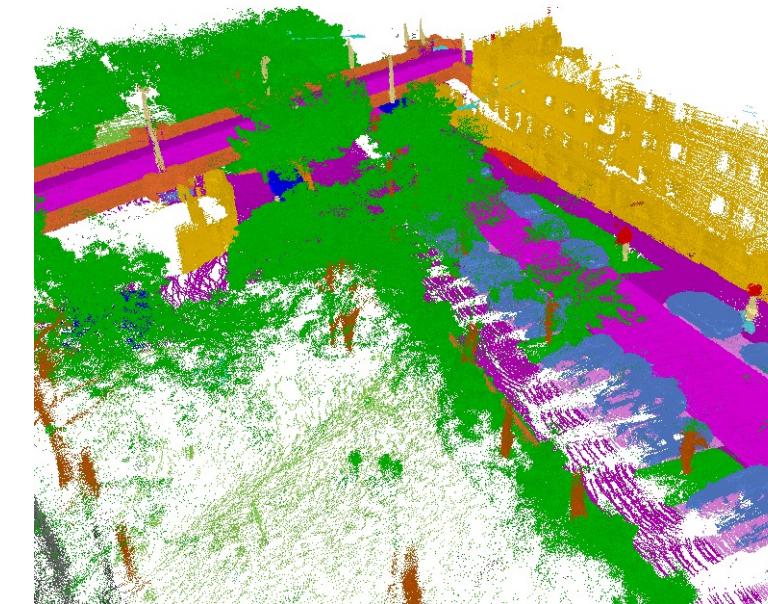


- Segmentation + 3D再構成: 開発済み
- 事象検出 & 自動追跡・測定: Graph Network, Point Cloud, VLM

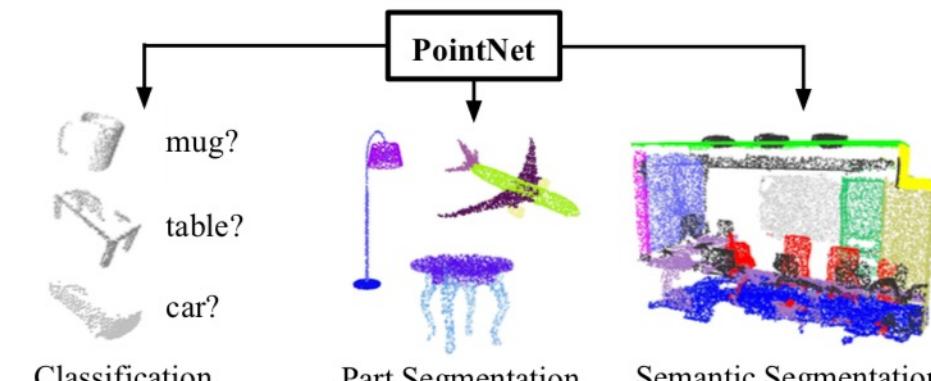
例: Point Cloud(点群解析)を活用した事象検出

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立教大谷山さんの修士論文: ~5倍の検出高速化



Hit pixel → point cloud



<https://arxiv.org/abs/4712.12033>

Ground truth



Prediction

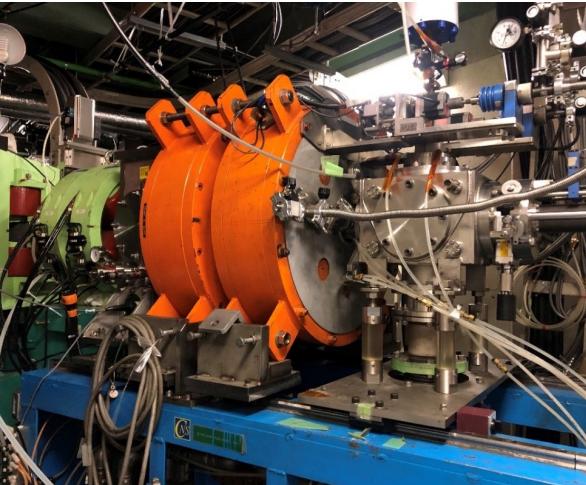
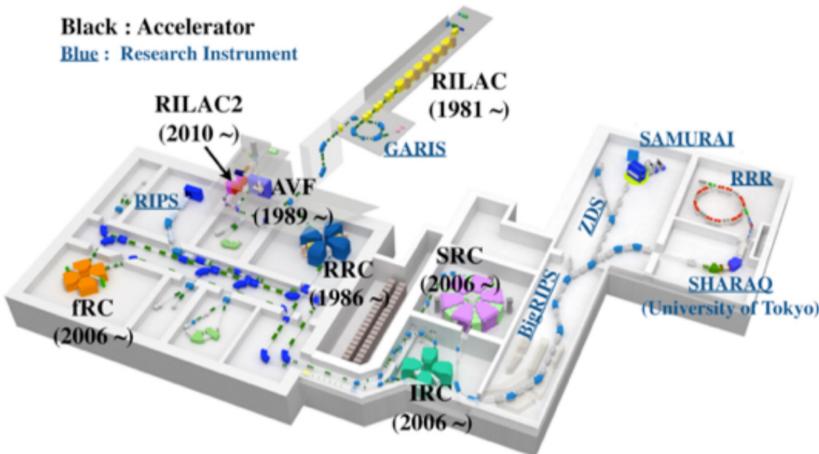


Dynamic Graph CNN for Learning on Point Clouds
<https://arxiv.org/abs/1801.07829>



- ・深層学習・機械学習: 解析にモデルをどう使うのか?
- ・素粒子・原子核物理解析への適用(レビュー)
- ・原子核乾板画像解析への深層学習の適用
- ・拡張・応用と今後の展開

イオン源: 加速器実験の最上流 (実験の要)



14 GHz HyperECR
(東大CNS, RIKEN)
• 運転中: ビーム測定不可
• オペレータの経験と勘

操作パラメーター

- ✓ マイクロ波出力
- ✓ ミラーコイル電流
- ✓ イオン化ガス圧
- ✓ サポートガス圧
- ✓ プランジャー位置
- ...

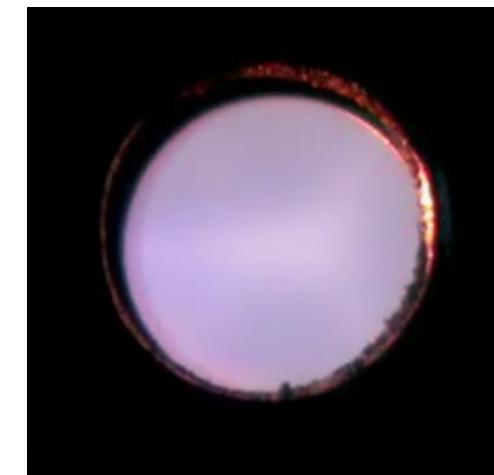
観測量

- ・マイクロ波反射
- ・真空度
- ・ドレイン電流
- + プラズマ光

隠れた物理状態

- 電子密度・温度
- イオン閉じ込め時間
- etc...

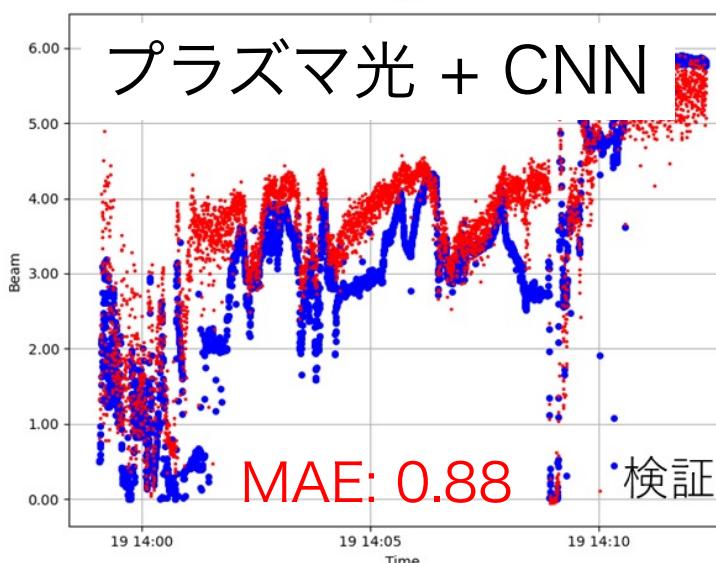
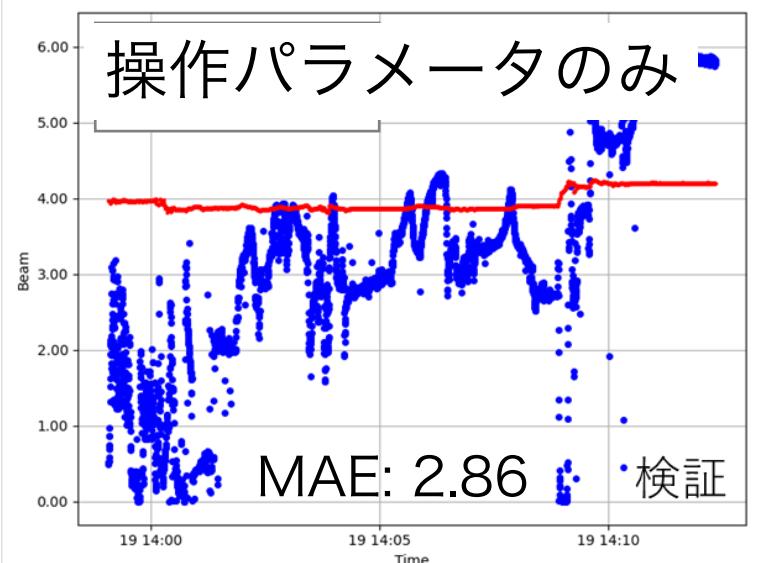
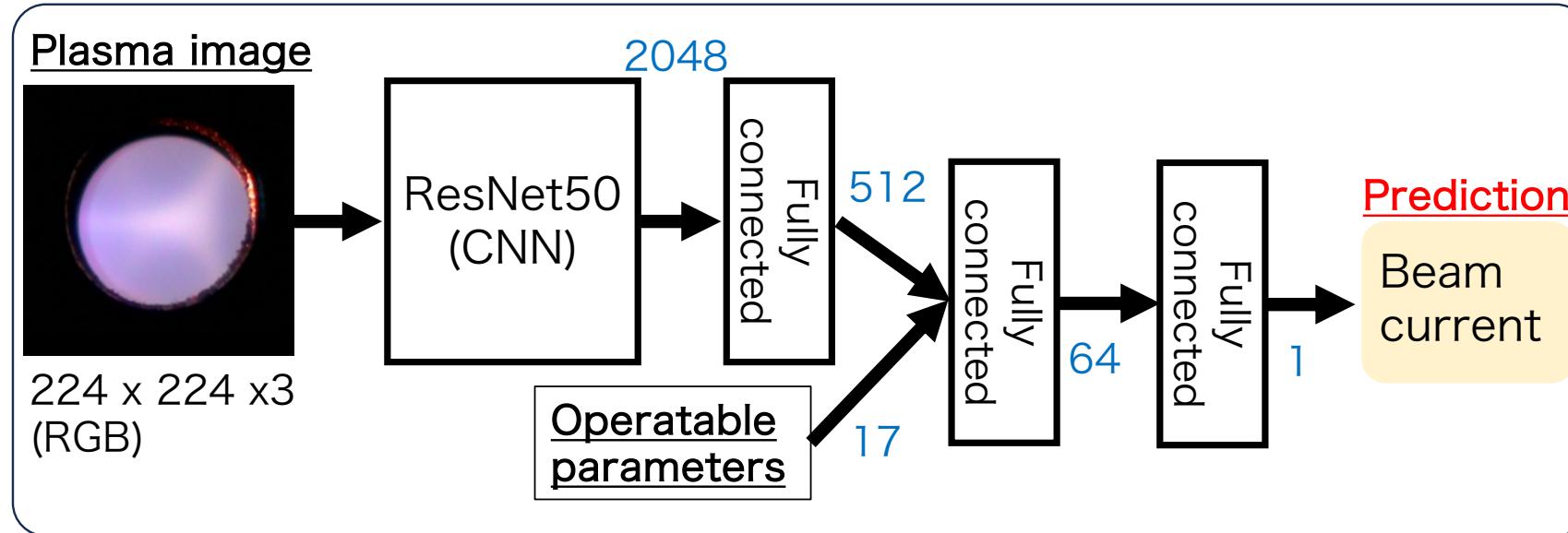
**ビーム強度
安定性**



Neural Networkに似ている?

某イオン源屋さん「プラズマ光でイオン源の機嫌がわかる」

CNNを用いた回帰モデルを訓練・検証

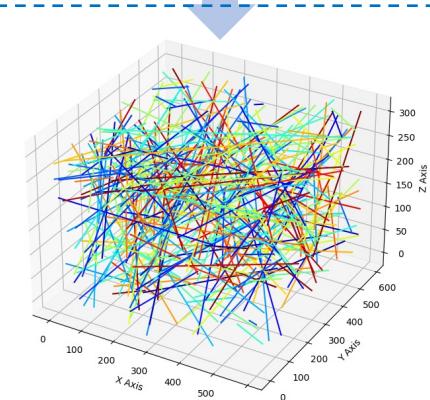
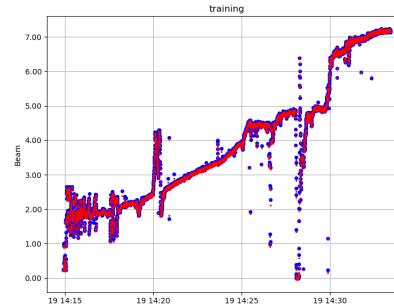
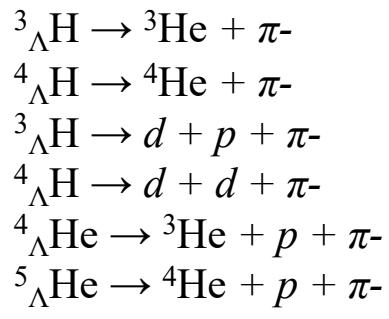


- ・ プラズマ画像 \leftrightarrow ビーム強度
 \rightarrow 特許出願済み
- ・ 実用化に向けた改善・評価
 \rightarrow RNN, 別のイオン種

独自のモダリティーで取得される実験データを高速解釈・解析

物理的解釈

- 生成崩壊形式・ビーム量変化



実験測定量

- Hitパターン・イオン源プラズマ光

pepper the aussie pup

キャプション

Text Encoder

類似度検索・異常検知

$T_1, T_2, T_3, \dots, T_N$



画像

Image Encoder

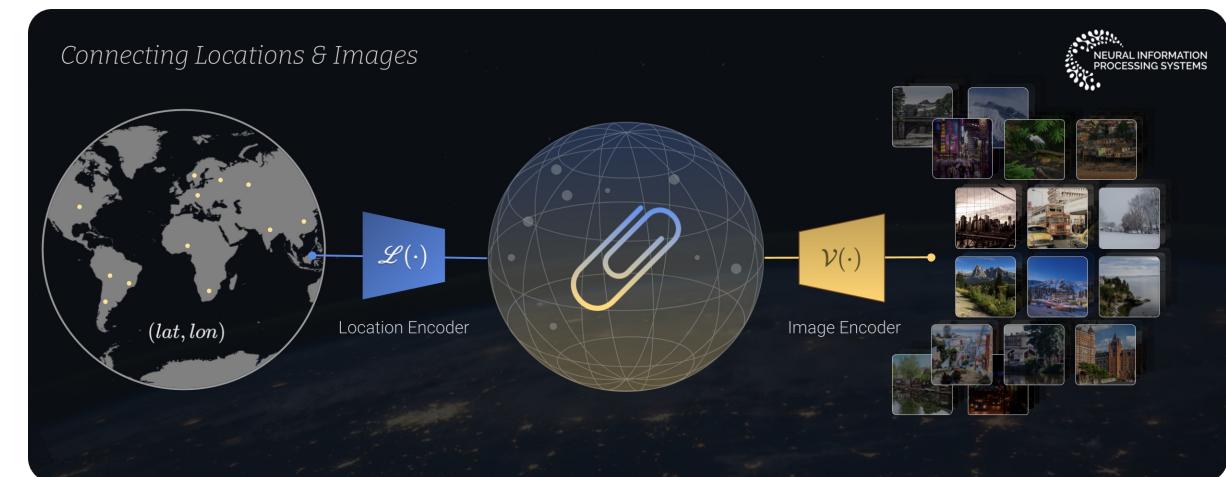
I_1	$I_1 \cdot T_1$	$I_1 \cdot T_2$	$I_1 \cdot T_3$	\dots	$I_1 \cdot T_N$
I_2	$I_2 \cdot T_1$	$I_2 \cdot T_2$	$I_2 \cdot T_3$	\dots	$I_2 \cdot T_N$
I_3	$I_3 \cdot T_1$	$I_3 \cdot T_2$	$I_3 \cdot T_3$	\dots	$I_3 \cdot T_N$
\vdots	\vdots	\vdots	\vdots	\ddots	\vdots
I_N	$I_N \cdot T_1$	$I_N \cdot T_2$	$I_N \cdot T_3$	\dots	$I_N \cdot T_N$

<https://openai.com>

Vision-Language Modelの活用例

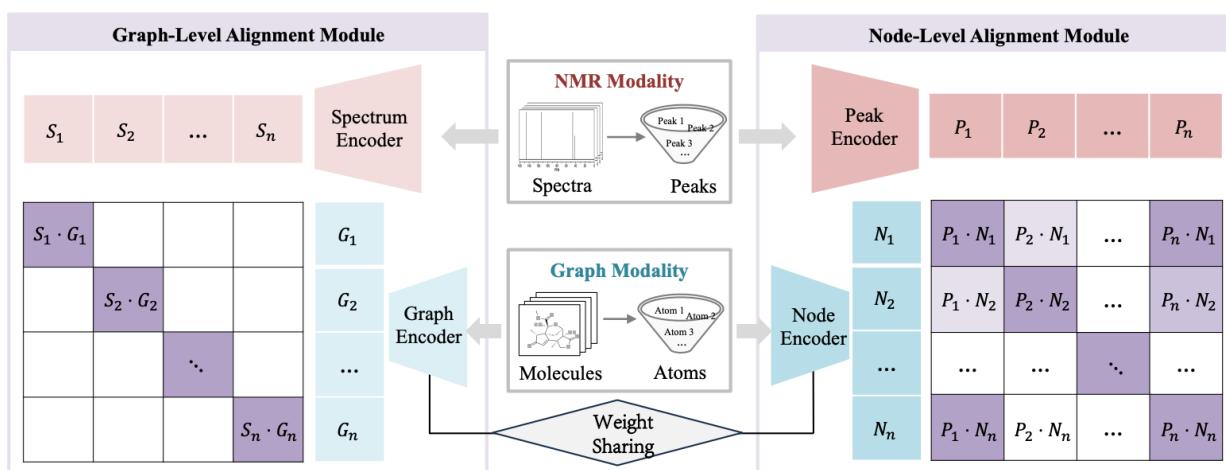
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GeoCLIP (NeurIPS 2023): GPS座標と自然画像



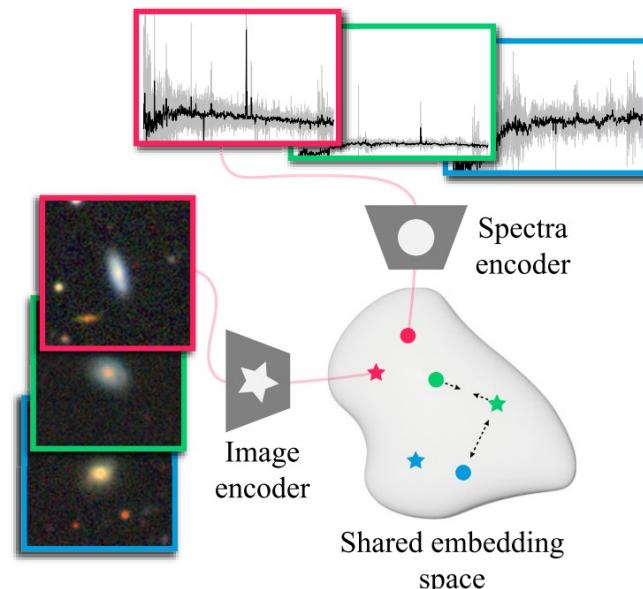
<https://github.com/VicenteVivan/geo-clip>

化学: NMR スペクトルと分子構造(2023)



[arXiv:2311.13817v4](https://arxiv.org/abs/2311.13817v4)

Astro-CLIP: 銀河画像とスペクトル (2024)



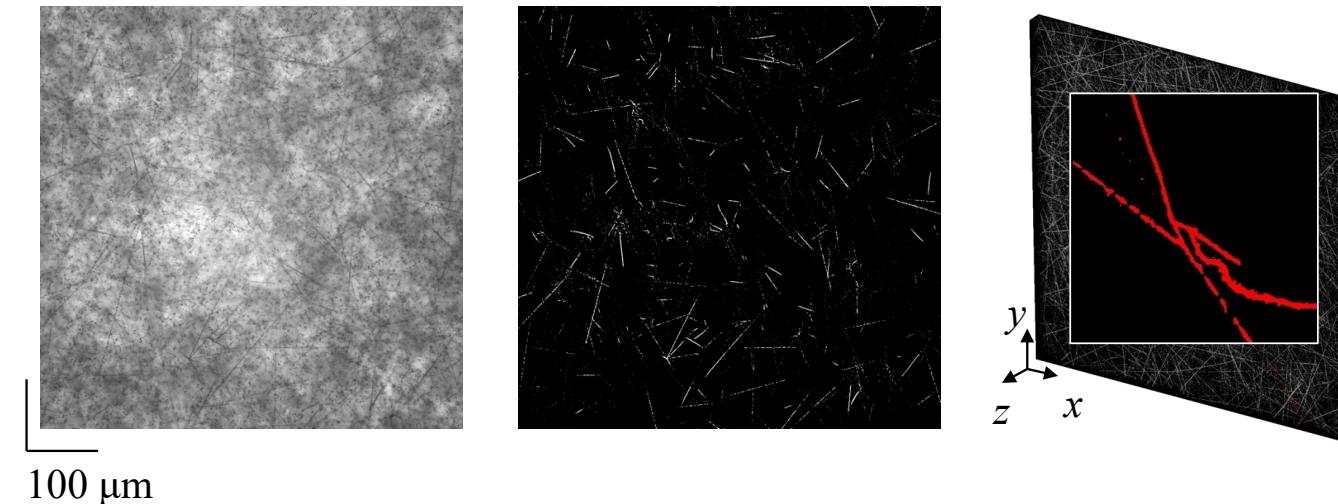
- タスク
- (1)類似度
 - (2)赤方偏移予測
 - (3)構成推測
 - (4)形状推測

<https://doi.org/10.1093/mnras/stae1450>

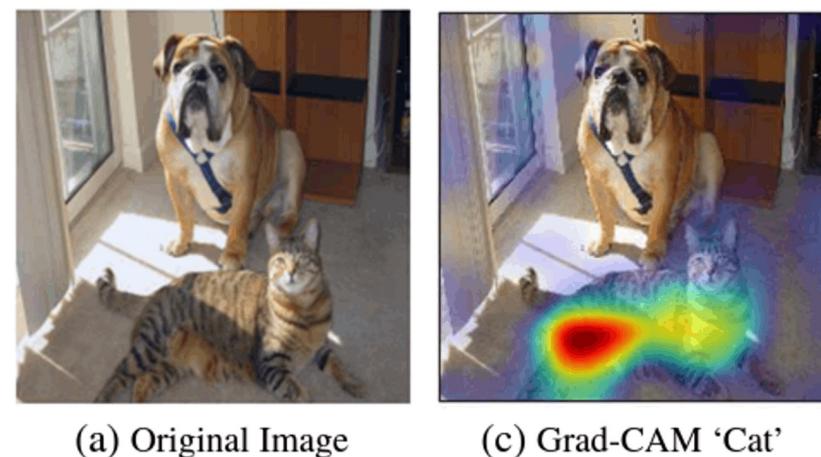
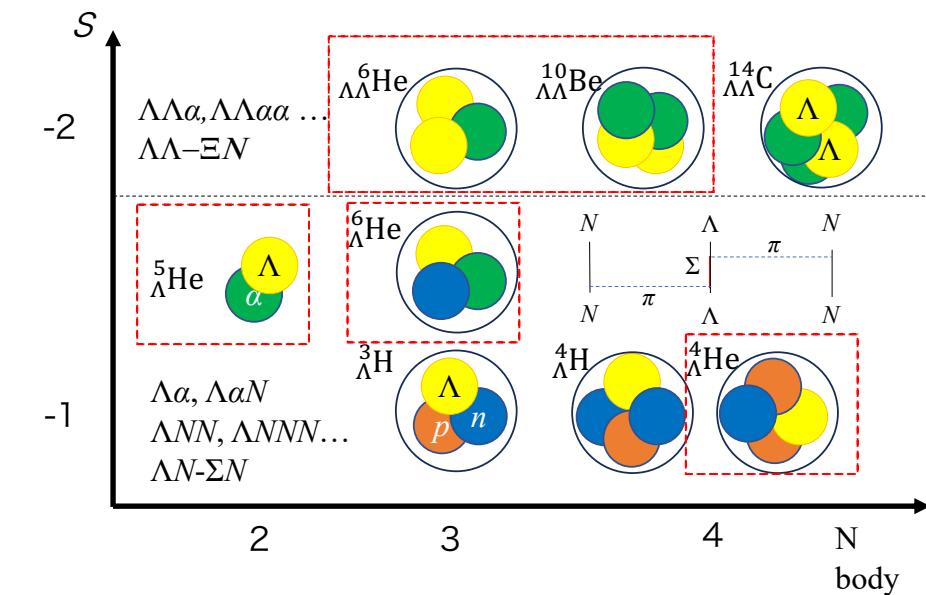
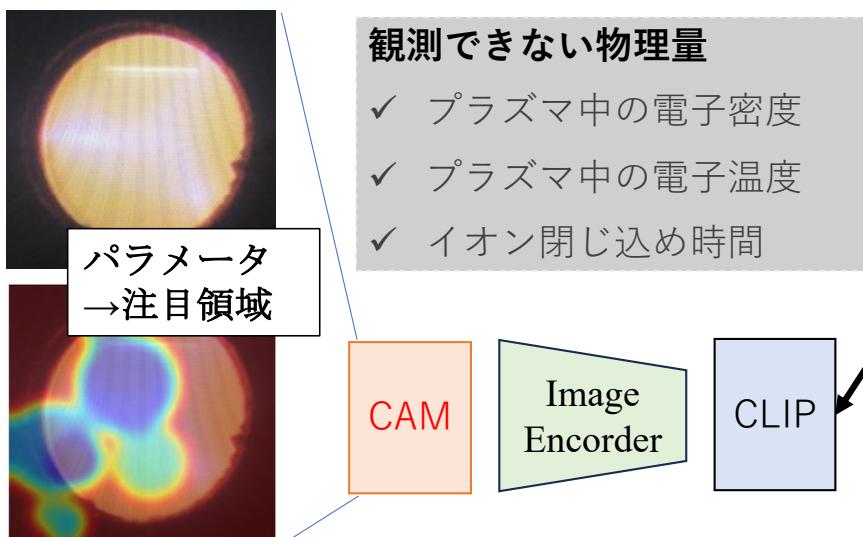
CLIP原論文

「抽象的な画像では精度が出ない」
→ 最近は克服されている！

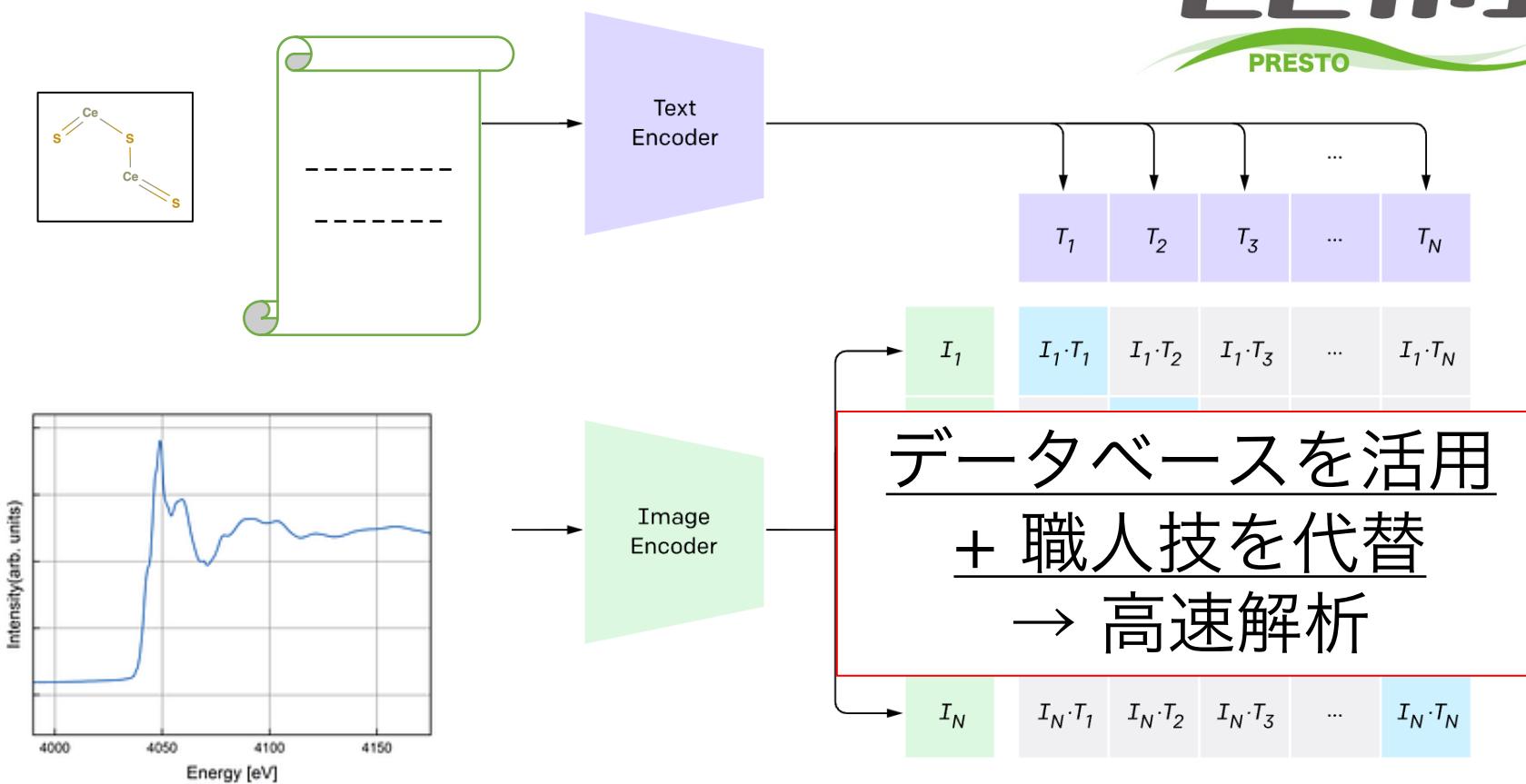
Segmentationによる飛跡抽出・3D再構成: 実データ \leftrightarrow Simulation



イオン源画像と数値パラメータ解釈



X線吸収スペクトル解析(XAFS) + マルチモーダル深層学習



JST さきがけ「計測解析基盤」採択
基礎物理・材料応用を深層学習でつなげる

- 独自の測定データ解析に対する深層学習の適用
- 素粒子・原子核実験解析への先行研究タスク・訓練データの定義、アキテクチャ選定
- 原子核乾板画像解析への深層学習の適用
 - 分類, 画像生成, 物体検出: 稀事象の自動検出を実現
 - 多様な事象へのRobustな解析手法開発
- 拡張・応用と今後の展開
 - イオン源自動制御に向けた画像解析深層学習の適用
 - マルチモーダル解析: Vision Language modelの活用

JSPS KAKENHI

JP25H00404, JP16H02180, JP20H00155, JP18H05403, JP19H05147, JP25H01550,
JP25K17415, JP23K19051

Proyectos I+D+i 2020 (ref: PID2020-118009GA-I00); Proyectos I+D+i 2022 (ref: PID2022-140162NB-I00); and Proyecto Consolidación Investigadora 2022 (ref: CNS2022-135768); as well as from Grants 2019-T1/TIC-13194 and 2023-5A/TIC-28925 under the Atracción de Talento Investigador program of the Community of Madrid.

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backup