Laboratory of Computational Physics - Module A

Advanced DQM for a Drift Tube Detector

Group 13:

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GitHub repository

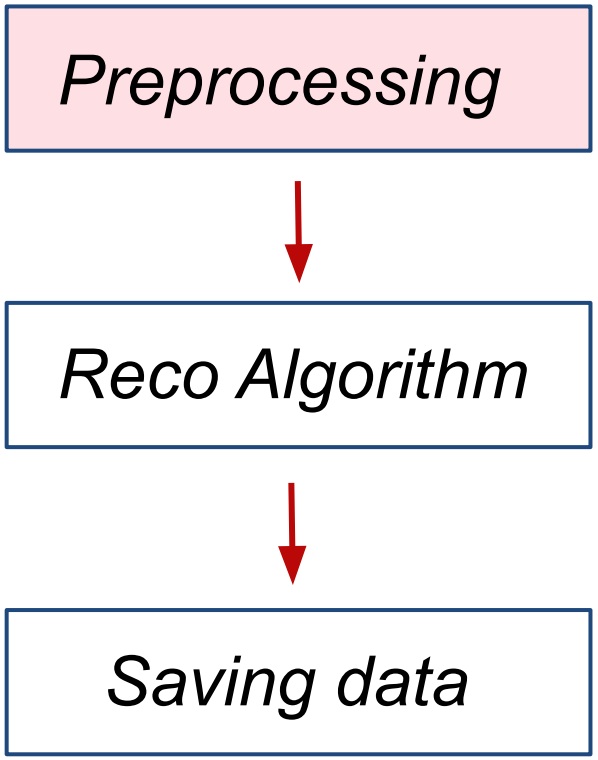
Project outline

Starting for data acquired by a cosmic muon detector of drift tubes at Legnaro laboratories we focused on:

- **building an output dataset** with **drift time** and **crossing angle** of the muon track as features
- **optimizing** the **reconstruction procedure** to obtain a more efficient and reproducible routine
- **studying** the **correlation** between these two features
- **testing** the performance of **NPLM** using the output dataset

Building the dataset

Building the dataset *outline*



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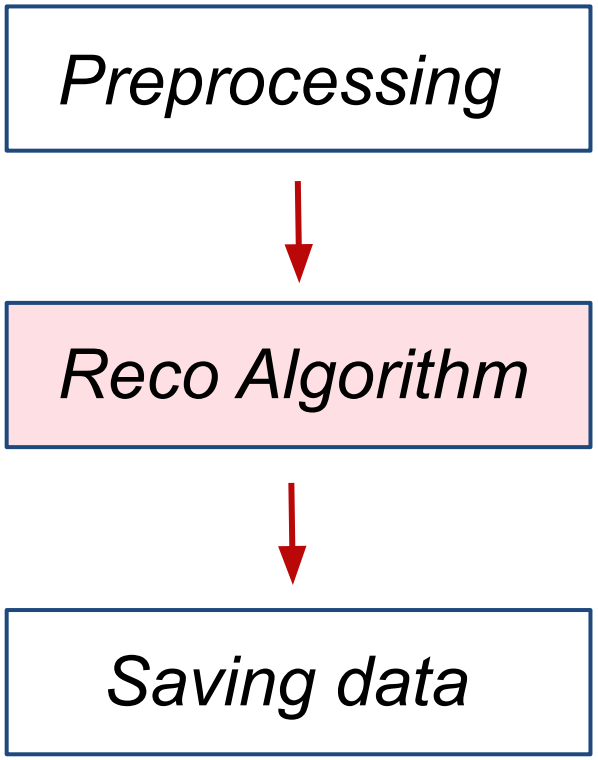

Building the dataset *outline*

Preprocessing

↓

Reco Algorithm

↓

Saving data

Preprocessing *the path from raw to readable data*

	HEAD	FPGA	TDC_CHANNEL	ORBIT_CNT	BX_COUNTER	TDC_MEAS
0	2	0	35	1379482729	2693	11
1	2	0	56	1379482738	3051	1
2	2	1	122	1379482739	567	12
3	2	0	98	1379482743	3196	23
4	2	0	101	1379482743	3201	13

	FPGA	TDC_CHANNEL	ORBIT_CNT	SL	LAYER	WIRE_X_LOC	WIRE_Z_LOC	HIT_DRIFT_TIME	X_LEFT_GLOB	X_RIGHT_GLOB
0	0	100	1379484750	0	4	63.0	19.5	-5.07	63.27	62.73
1	1	35	1379484750	2	1	42.0	-19.5	43.60	39.65	44.35
2	0	101	1379484750	0	2	63.0	-6.5	45.77	60.54	65.46
3	1	81	1379484750	3	2	-147.0	-6.5	107.27	-152.78	-141.22
4	0	38	1379484750	1	3	84.0	6.5	96.43	78.81	89.19

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```
# SL column
# sl -> 0: fpga 0 tdc_ch in [64, 127]; sl -> 1: fpga 0 tdc_ch in [0, 63]
# sl -> 2: fpga 1 tdc_ch in [0, 63];   sl -> 3: fpga 1 tdc_ch in [64, 127]
df["SL"] = (df["TDC_CHANNEL"] + 128*df["FPGA"]) // 64
df["SL"][df["SL"] < 2] = [int(not x) for x in df["SL"]]

# LAYER column
df.loc[(df["TDC_CHANNEL"] % 4 == 0), "LAYER"] = 4
df.loc[(df["TDC_CHANNEL"] % 4 == 2), "LAYER"] = 3
df.loc[(df["TDC_CHANNEL"] % 4 == 1), "LAYER"] = 2
df.loc[(df["TDC_CHANNEL"] % 4 == 3), "LAYER"] = 1

# assign the wire position
for layer in [1, 2, 3, 4]:
    # local wire x position
    df.loc[df["LAYER"] == layer, "WIRE_X_LOC"] = (df["TDC_CHANNEL"] % 64 // 4) * XCELL + X_POS_SHIFT[layer]

    # local wire z position
    df.loc[df["LAYER"] == layer, "WIRE_Z_LOC"] = Z_POS_SHIFT[layer]
```

Preprocessing *the path from raw to readable data*

	FPGA	TDC_CHANNEL	ORBIT_CNT	SL	LAYER	WIRE_X_LOC	WIRE_Z_LOC	HIT_DRIFT_TIME	X_LEFT_GLOB	X_RIGHT_GLOB
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```
# HIT_DRIFT_TIME column
df["HIT_DRIFT_TIME"] = (df["BX_COUNTER"] + df["TDC_MEAS"]/30)*DURATION_BX - df["T0_NS"]

# Left, right hit positions
df["X_LEFT_GLOB"]  = df["WIRE_X_GLOB"] - df["HIT_DRIFT_TIME"]*VDRIFT
df["X_RIGHT_GLOB"] = df["WIRE_X_GLOB"] + df["HIT_DRIFT_TIME"]*VDRIFT
```

Preprocessing *the path from raw to readable data*

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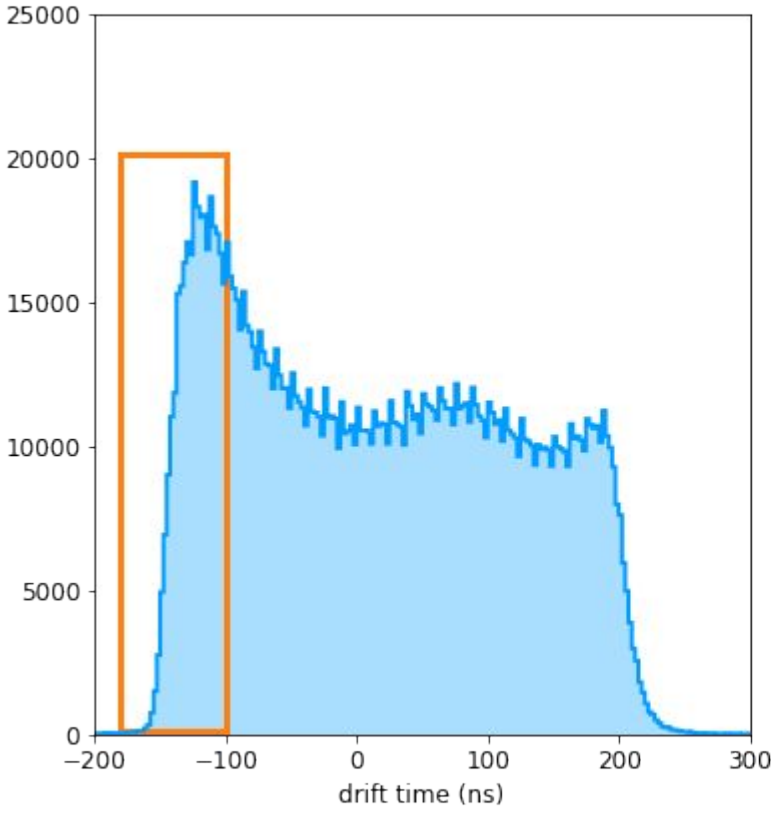
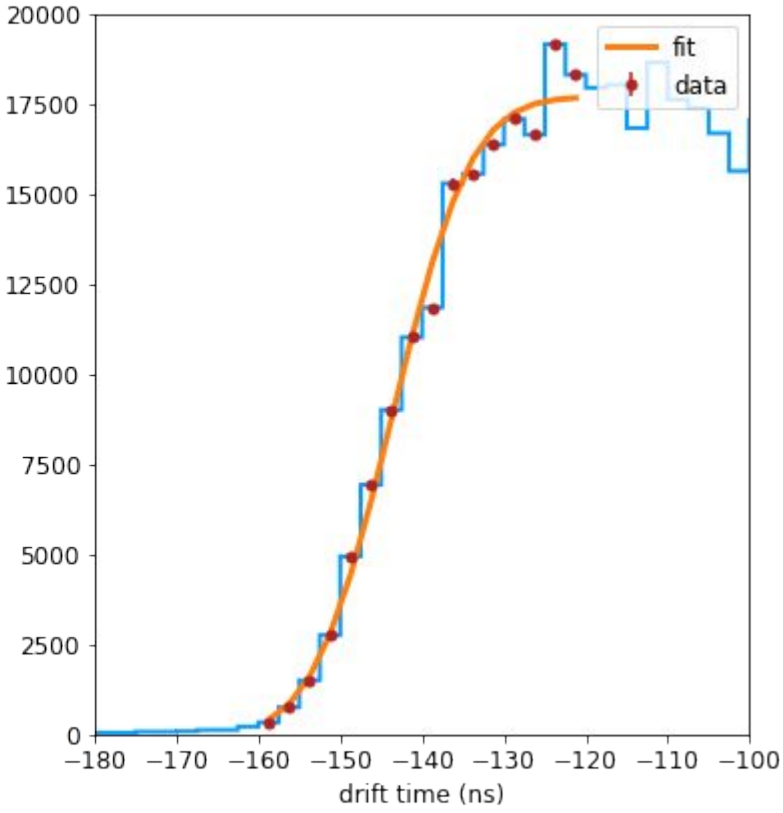
df["X_LEFT_GLOB"]  = df["WIRE_X_GLOB"] - df["HIT_DRIFT_TIME"]*VDRIFT
df["X_RIGHT_GLOB"] = df["WIRE_X_GLOB"] + df["HIT_DRIFT_TIME"]*VDRIFT
```

$$T_0 = T_{\text{scint}} + T_{\text{scint\_offset}}$$

Preprocessing *the path from raw to readable data*

$$f(t) = \frac{1}{2} I \left[1 + \mathrm{erf}\left(\frac{t - \bar{t}}{\sqrt{2}\sigma} \right) \right] \rightarrow T_{\mathrm{scint\_offset}} = \bar{t} - k \cdot \sigma$$





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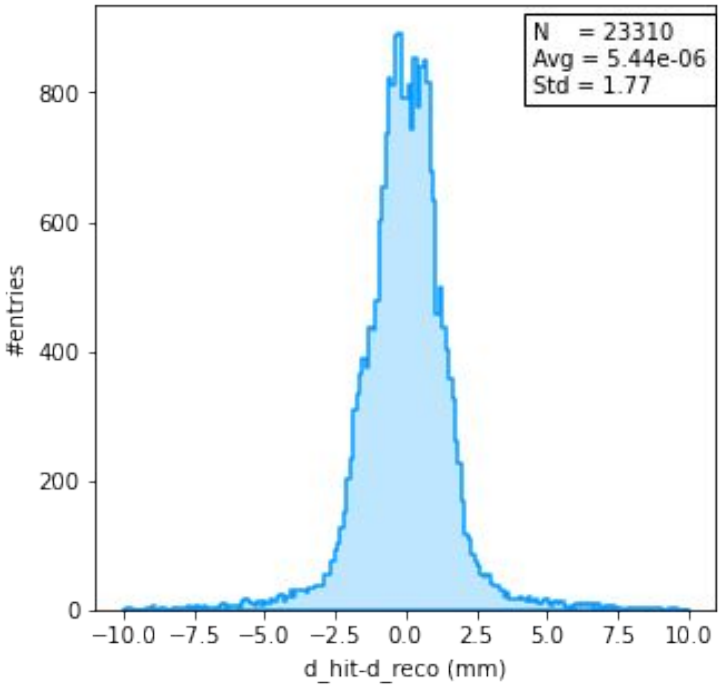
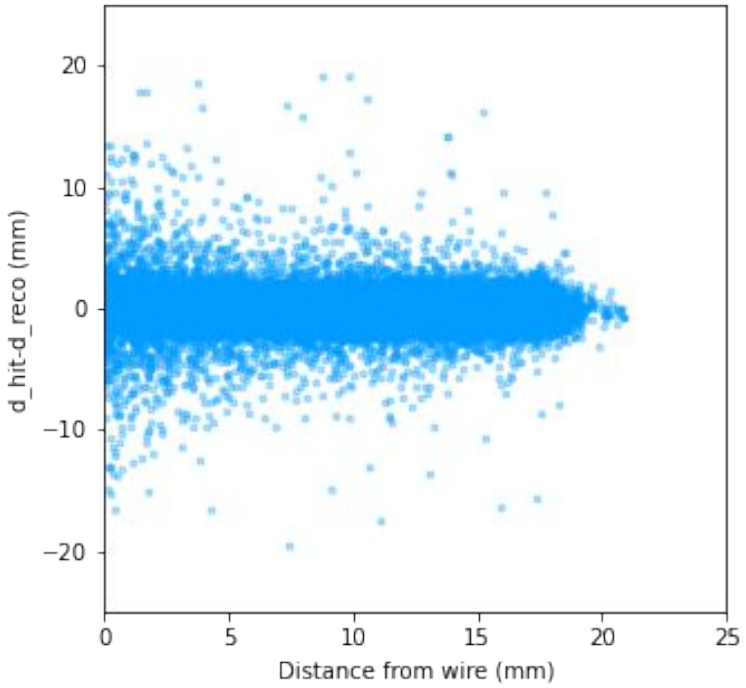
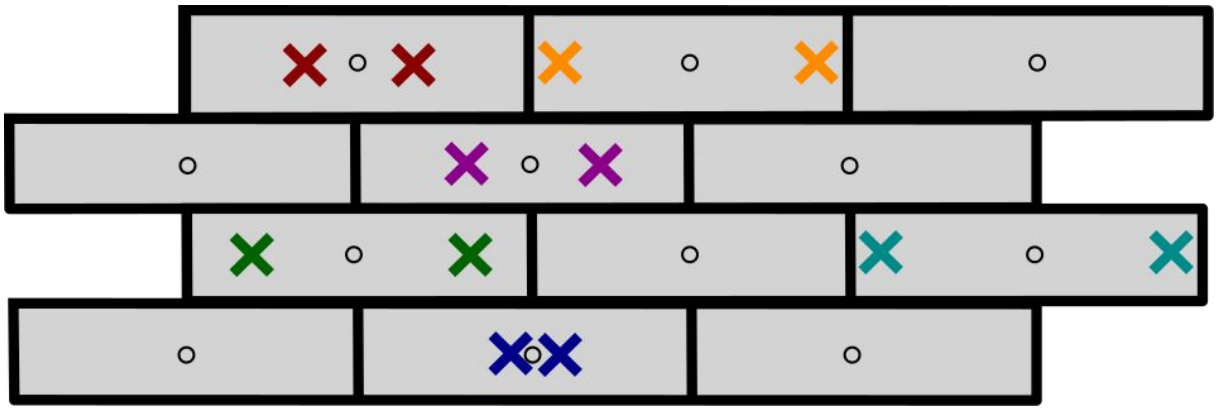




Reco Algorithm *first combinatorial step*



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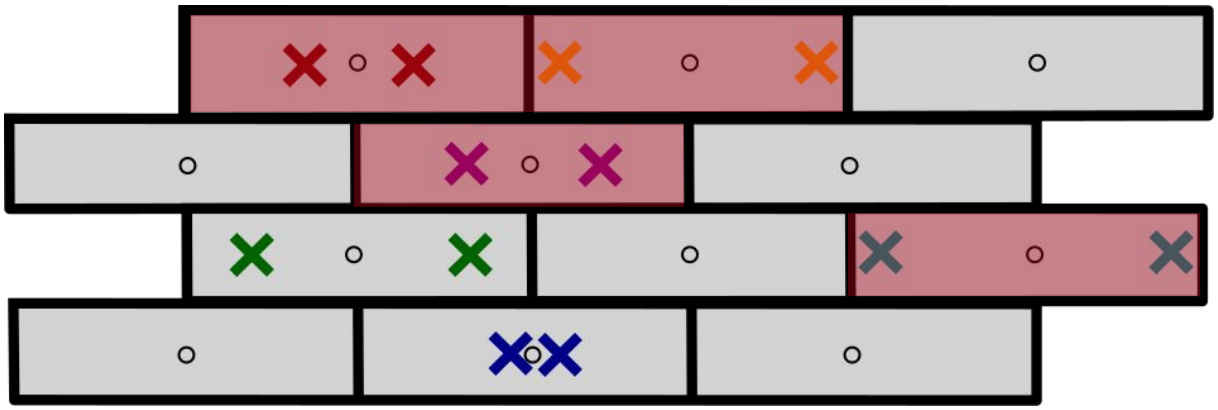

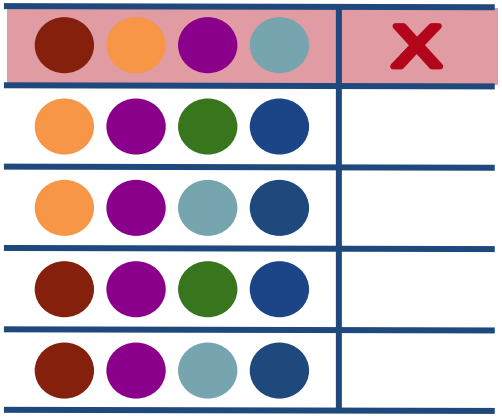

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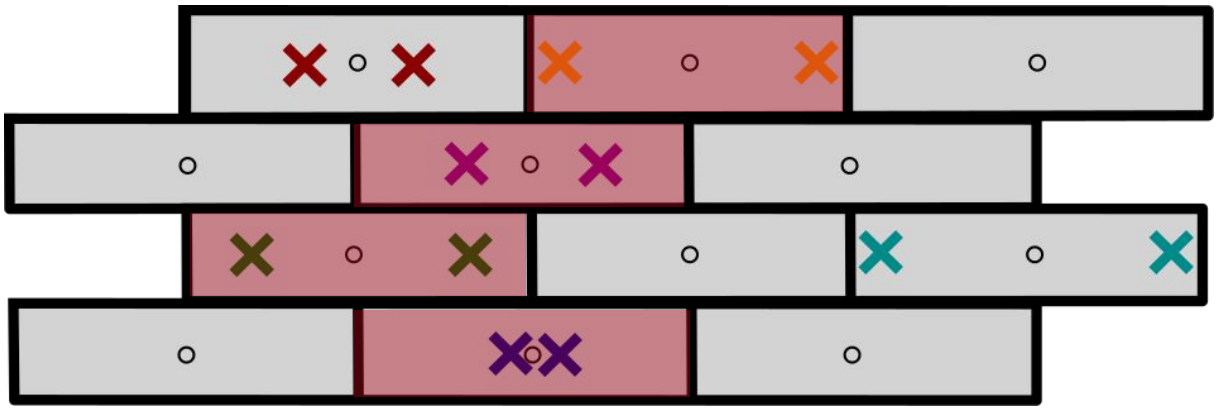

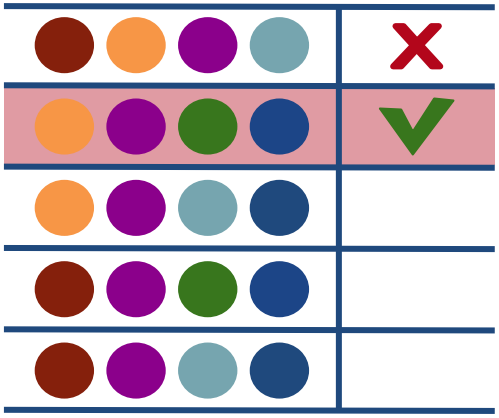

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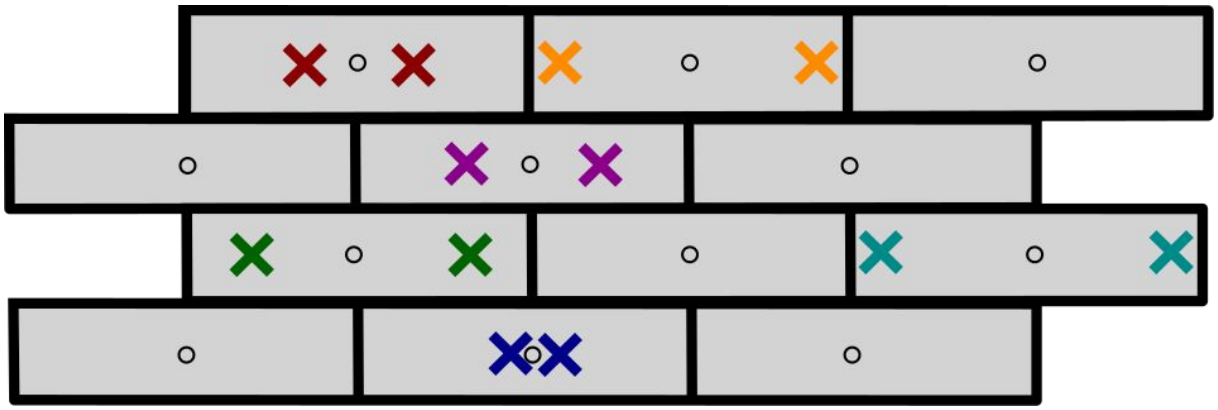

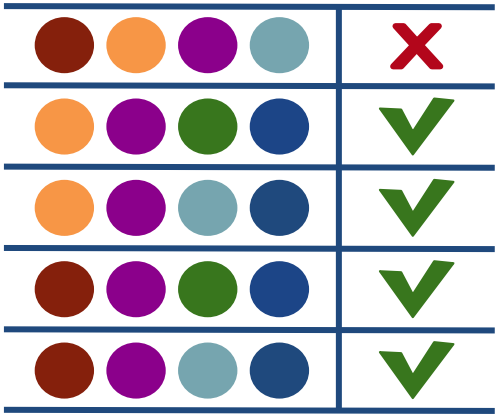

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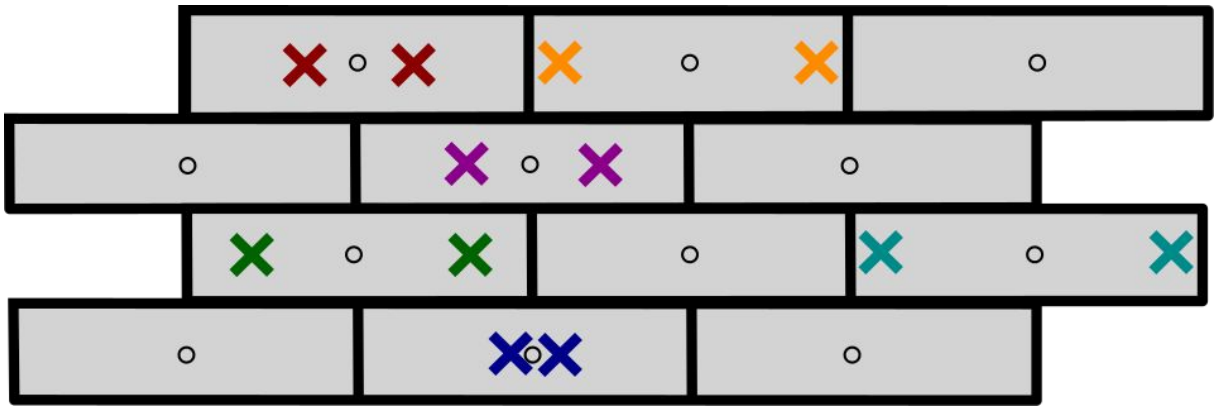
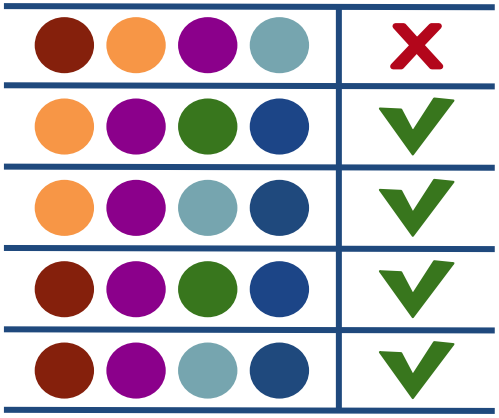
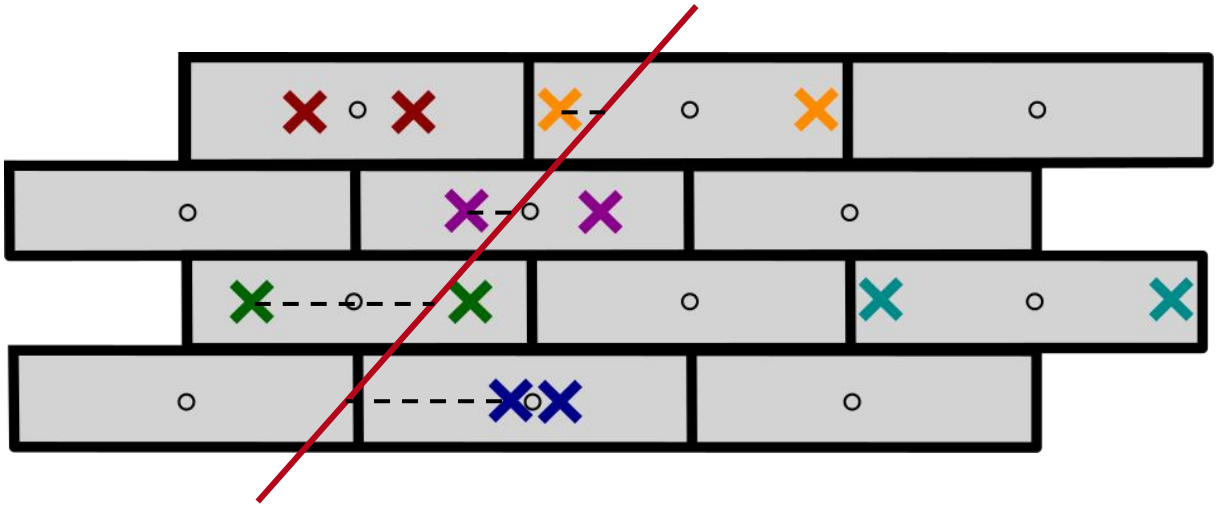
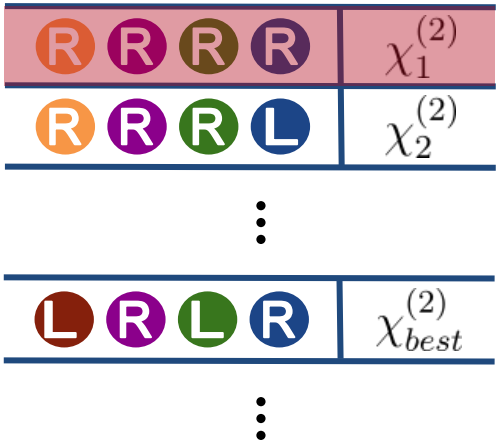




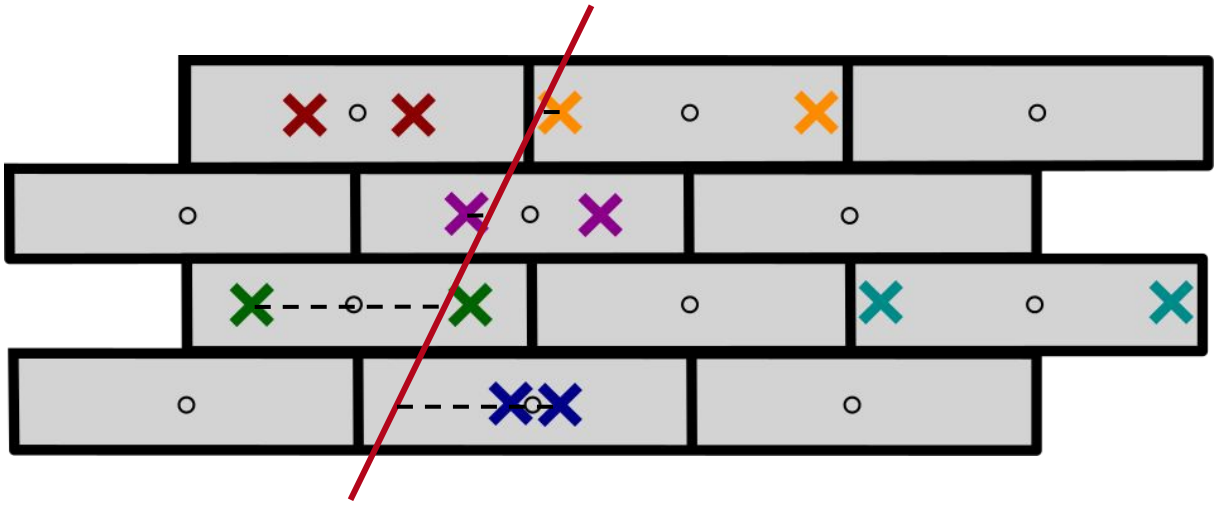
```
comb = []
    if len(df.LAYER.unique()) == 3:
        comb.append(df)
        tot_Hits = 3
    else:
        for index in list(combinations(df.index, 4)):
            if len(df.loc[index, :].LAYER.unique()) == 4:
                comb.append(df.loc[index, :])
        tot_Hits = 4
```

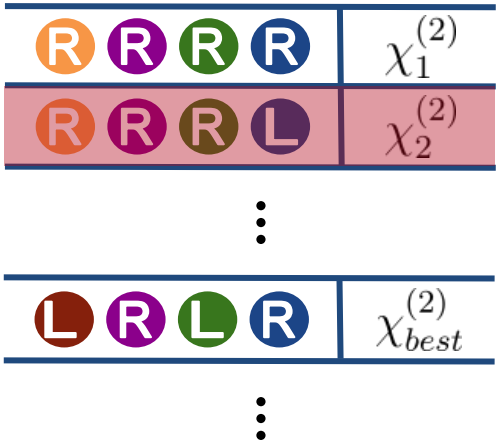
Reco Algorithm *second combinatorial step*



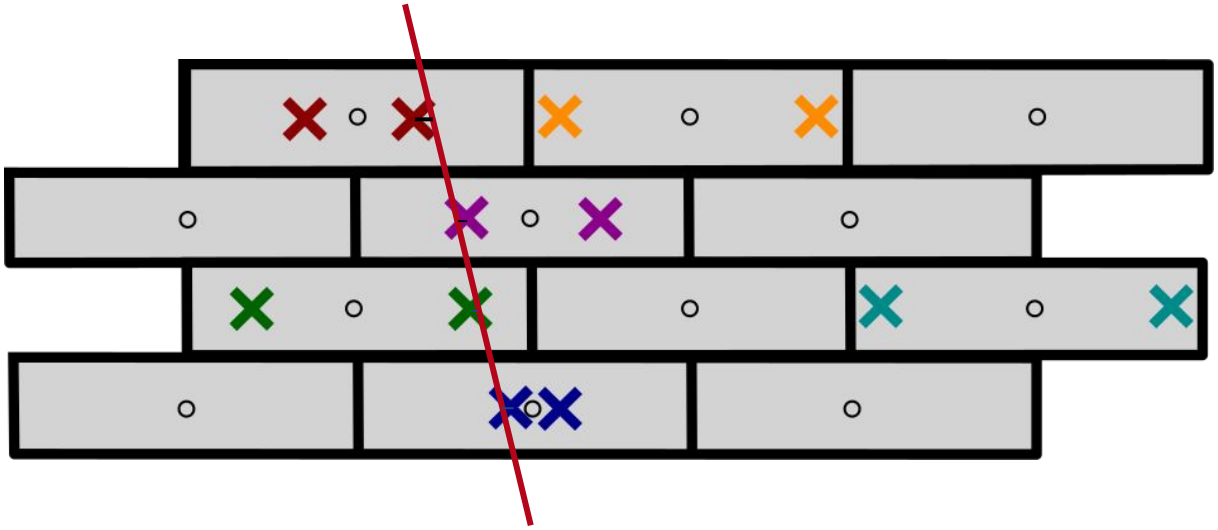


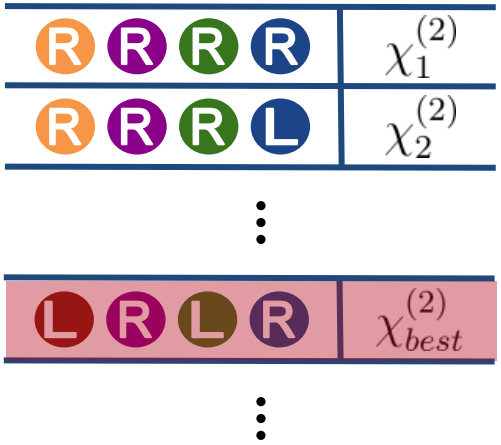
Reco Algorithm *second combinatorial step*





Reco Algorithm *second combinatorial step*





$$\min_{i \in \{2^{nd}\ step\ combinations\}} \frac{|\chi^{(2)}_i - d.o.f.|}{\sqrt{2d.o.f.}}$$

best combination

Reco Algorithm *second combinatorial step*

```
min_lambda = np.finfo(float).max

 for data in comb:
     X = np.array(pd.concat([data["X_RIGHT_GLOB"], data["X_LEFT_GLOB"]]))
     Y = np.array(pd.concat([data["WIRE_Z_GLOB"], data["WIRE_Z_GLOB"]]))
     for indexes_comb in list(combinations(range(len(X)), tot_Hits)):
         indexes_comb = list(indexes_comb)
         if len(np.unique(Y[indexes_comb])) == tot_Hits:
             regr_dict = linear_reg(X[indexes_comb], Y[indexes_comb])
             if abs(regr_dict["chisq_comp"]) < min_lambda:
                 min_lambda = abs(regr_dict["chisq_comp"])
                 xdata = X[indexes_comb]
                 res_dict = regr_dict
                 best_comb = indexes_comb
                 best_data = data
```

Output dataset

	SL	CH	HIT_DRIFT_TIME	D_WIRE_HIT	m	THETA
0	0	100	-5.066667	0.272821	-0.127657	-7.274849
1	0	100	149.100000	8.028462	-0.171659	-9.740392
2	0	100	79.933333	-4.304103	-1.141815	-48.788159
3	0	100	32.433333	-1.746410	-0.144280	-8.209984
4	0	100	39.933333	2.150256	0.209862	11.852203

```
def saveChannels(df, OUTPUT_PATH, RUNNUMBER):

    FILE_NAME = f"RUN00{RUNNUMBER}_channels.h5"
    save_to = OUTPUT_PATH + FILE_NAME

    print("Saving data...")

    for sl in np.unique(df["SL"]):
        for channel in np.unique(df[df["SL"] == sl]["CH"]):
            df[(df["SL"] == sl) & (df["CH"] == channel)].to_hdf(save_to, key=f"sl{sl}/ch{channel}", mode="a")

    return
```

Optimization

Problems

Problems detected

RAM usage

On Linux use also swap memory

- slow computation
- on large datasets process killed by OS due to RAM overuse

Computation time

- slow reading DataFrame from file
- slow mapping
- slow reconstruction due to single process

Let's analyze each problematic module

`mappings.py` *not optimized*

```python
# set the wire num inside the layer: ranging from 1 to 16 (left to right)
# in tdc_channel_norm the channel is normalized from 0->63 for each sl
df["TDC_CHANNEL_NORM"] = df["TDC_CHANNEL"] % 64   # .astype(np.uint8)
df["WIRE_NUM"] = df["TDC_CHANNEL_NORM"] // 4 + 1  # .astype(np.uint8)

# assign the wire position
for layer in [1, 2, 3, 4]:
    # local wire x position
    df.loc[df["LAYER"] == layer, "WIRE_X_LOC"] = (
        df["WIRE_NUM"] - 1
    ) * XCELL + X_POS_SHIFT[layer]

    # local wire z position
    df.loc[df["LAYER"] == layer, "WIRE_Z_LOC"] = Z_POS_SHIFT[layer]

df = df.astype({"SL": "int8", "LAYER": "int8"})
return df
```

useless columns in DataFrame

↓

more RAM occupied

conversion to `uint8` as last operation

↓

deal with bigger size `DataFrame` in for loop

mappings.py *optimized*

```
df = df.astype({"SL": "uint8", "LAYER": "uint8"})
# set the wire num inside the layer: ranging from 1 to 16 (left to right)
# tdc_channel is normalized from 0->63 for each sl
# assign the wire position
for layer in [1, 2, 3, 4]:
    # local wire x position
    df.loc[df["LAYER"] == layer, "WIRE_X_LOC"] = (
        df["TDC_CHANNEL"] % 64 // 4
    ) * XCELL + X_POS_SHIFT[layer]

    # local wire z position
    df.loc[df["LAYER"] == layer, "WIRE_Z_LOC"] = Z_POS_SHIFT[layer]

return df
```

Not Optimized*:

- RAM: 12.85 MB
- Time: 0.061 s

Optimized*:

- RAM: 8.71 MB
- Time: 0.066 s

*On ⅓ of 000054 dataset

EventsFactory.py *not optimized*

```python
def getEvents(stream_df, cfg, runTimeShift):

    # create a dataframe with only valid hits->trig words and scint hits removed
    hits_df = stream_df[
        (stream_df.HEAD == cfg["headers"]["valid_hit"]) &
        (stream_df.TDC_CHANNEL <= 127)].copy()

    # fix TDC_MEAS data type
    hits_df = hits_df.dropna()
    hit

    # c
    map
    hit

    # s
    # t

    trigger_df = stream_df[
        (stream_df["HEAD"] == cfg["scintillator"]["head"]) &
        (stream_df["FPGA"] == cfg["scintillator"]["fpga"]) &
        (stream_df["TDC_CHANNEL"] == cfg["scintillator"]["tdc_ch"])].copy()

    # create a T0 column (in ns)
    trigger_df["T0"] = (trigger_df["BX_COUNTER"] + trigger_df["TDC_MEAS"] / 30)

    # select only hits in the same orbit of a scint trigger signal
    hit
        pd.merge(


    )
    # p
    pri

    # c
    hits_df_["T0_NS"] = hits_df_["T0"] * DURATION_BX

    for sl, offset_sl in cfg["time_offset_sl"].items():
        # correction is in the form:
        # coarse offset valid for all SL + fine tuning
        hits_df_.loc[
            hits_df_["SL"] == sl, "T0_NS"
        ] -= cfg["time_offset_scint"] -runTimeShift + offset_sl # 6 for 123, 8 for 0

    hits_df_ = map_hit_position(hits_df_, local=False)

    return computeEvents(hits_df_)
```

```python
hits_df = stream_df[
    (stream_df.HEAD == cfg["headers"]["valid_hit"]) &
    (stream_df.TDC_CHANNEL <= 127)].copy()
```

```python
trigger_df = stream_df[
    (stream_df["HEAD"] == cfg["scintillator"]["head"]) &
    (stream_df["FPGA"] == cfg["scintillator"]["fpga"]) &
    (stream_df["TDC_CHANNEL"] == cfg["scintillator"]["tdc_ch"])].copy()
```

create a copy of a subset of a DataFrame

↓

more RAM occupied.
Can be avoided?

EventsFactory.py *not optimized*

```python
def getEvents(stream_df, cfg, runTimeShift):

    # create a dataframe with only valid hits->trig words and scint hits removed
    hits_df = stream_df[
        (stream_df.HEAD == cfg["headers"]["valid_hit"]) &
        (stream_df.TDC_CHANNEL <= 127)].copy()

    # fix TDC_MEAS data type
    hits_df = hits_df.dropna()
    hits_df = hits_df.astype({"TDC_MEAS": "int32"})

    # create mapping with the loaded configurations
    mapper = Mapping(cfg)
    hits_df = mapper.global_map(hits_df)

    # select all orbits with a trigger signal from
    # the scintillators coincidence

    # select only hits in the same orbit of a scint trigger signal
    hits_df_ = pd.merge(
        hits_df, trigger_df[["ORBIT_CNT","T0"]],
        left_on="ORBIT_CNT", right_on="ORBIT_CNT",
        suffixes=(None, None)
    )
    # print the number of valid hits found in data
    print(f"Valid hits: {hits_df_.shape[0]}")

    # create a time column in NS
    hits_df_["T0_NS"] = hits_df_["T0"] * DURATION_BX

    for sl, offset_sl in cfg["time_offset_sl"].items():
        # correction is in the form:
        # coarse offset valid for all SL + fine tuning
        hits_df_.loc[
            hits_df_["SL"] == sl, "T0_NS"
        ] -= cfg["time_offset_scint"] -runTimeShift + offset_sl # 6 for 123, 8 for 0

    hits_df_ = map_hit_position(hits_df_, local=False)

    return computeEvents(hits_df_)
```

`.dropna()` method creates a new `DataFrame`;
`.astype()` requires time to resize memory blocks for dataset

more computation time and RAM usage.
Can be done at reading from file time?

EventsFactory.py *not optimized*

```python
def getEvents(stream_df, cfg, runTimeShift):

    # create a dataframe with only valid hits->trig words and scint hits removed
    hits_df = stream_df[
        (stream_df.HEAD == cfg["headers"]["valid_hit"]) &
        (stream_df.TDC_CHANNEL <= 127)].copy()

    # fix TDC_MEAS data type
    hits_df = hits_df.dropna()
    hits_df = hits_df.astype({"TDC_MEAS": "int32"})

    # create mapping with the loaded configurations
    mapper = Mapping(cfg)
    hits_df = mapper.global_map(hits_df)

    # select all orbits with a trigger signal from
    # the scintillators coincidence
    trigger_df = stream_df[
        (stream_df["HEAD"] == cfg["scintillator"]["head"]) &
        (stream_df["FPGA"] == cfg["scintillator"]["fpga"]) &

    # print the number of valid hits found in data
    print(f"Valid hits: {hits_df_.shape[0]}")

    # create a time column in NS
    hits_df_["T0_NS"] = hits_df_["T0"] * DURATION_BX

    for sl, offset_sl in cfg["time_offset_sl"].items():
        # correction is in the form:
        # coarse offset valid for all SL + fine tuning
        hits_df_.loc[
            hits_df_["SL"] == sl, "T0_NS"
        ] -= cfg["time_offset_scint"] -runTimeShift + offset_sl # 6 for 123, 8 for 0

    hits_df_ = map_hit_position(hits_df_, local=False)

    return computeEvents(hits_df_)
```

mapping on DataFrame not completely filtered yet

↓

compute variables on useless rows. Can be avoided?

EventsFactory.py *not optimized*

```python
def getEvents(stream_df, cfg, runTimeShift):

    # create a dataframe with only valid hits->trig words and scint hits removed
    hits_df = stream_df[
        (stream_df.HEAD == cfg["headers"]["valid_hit"]) &
        (stream_df.TDC_CHANNEL <= 127)].copy()

    # create a T0 column (in ns)
    trigger_df["T0"] = (trigger_df["BX_COUNTER"] + trigger_df["TDC_MEAS"] / 30)

    # select all orbits with a trigger signal from
    # the scintillators coincidence
    trigger_df = stream_df[
        (stream_df["HEAD"] == cfg["scintillator"]["head"]) &
        (stream_df["FPGA"] == cfg["scintillator"]["fpga"]) &
        (stream_df["TDC_CHANNEL"] == cfg["scintillator"]["tdc_ch"])].copy()

    # create a T0 column (in ns)
    trigger_df["T0"] = (trigger_df["BX_COUNTER"] + trigger_df["TDC_MEAS"] / 30)

    # select only hits in the same orbit of a scint trigger signal
    hits_df_ = pd.merge(
        hits_df, trigger_df[["ORBIT_CNT","T0"]],
        left_on="ORBIT_CNT", right_on="ORBIT_CNT",
        suffixes=(None, None)
    )
    # print the number of valid hits found in data
    print(f"Valid hits: {hits_df_.shape[0]}")

    # create a time column in NS
    hits_df_["T0_NS"] = hits_df_["T0"] * DURATION_BX

    for sl, offset_sl in cfg["time_offset_sl"].items():
        # correction is in the form:

    # create a time column in NS
    hits_df_["T0_NS"] = hits_df_["T0"] * DURATION_BX
```

useless new column on DataFrame

↓

more RAM occupied

EventsFactory.py *not optimized*

```python
def computeEvents(hits_df_):
    events = []
    for x in pd.unique(hits_df_.ORBIT_CNT):
        events.append(hits_df_[hits_df_["ORBIT_CNT"] == x])
        events[-1] = events[-1].reset_index(drop=True)
    return events
```

use of non-`pandas` methods

↓

more RAM occupied and time consuming operations

EventsFactory.py *optimized*

```python
def getEvents(df_fname, cfg, runTimeShift):
    #reading df from file
    dtype_dict = { 'HEAD':np.uint8, 'FPGA':np.uint8, 'TDC_CHANNEL':np.uint8,
                   'ORBIT_CNT':np.uint64, 'BX_COUNTER':np.uint16, 'TDC_MEAS':np.uint8 }
    print("Reading dataset from file...")
    stream_df = pd.read_csv(df_fname, dtype=dtype_dict)
    #drop NaN
    stream_df.dropna(inplace=True)

    # create a dataframe with only valid hits- trig words and scint hits removed
    hits_df = stream_df[
        (stream_df.HEAD == cfg["header"]["valid_hit"]) &
        (stream_df.TDC_CHANNEL <= 127)]

    # select all orbits with a trigger signal from
    # the scintillators coincidence
    trigger_df = stream_df[
        (stream_df["HEAD"] == cfg["scintillator"]["head"]) &
        (stream_df["FPGA"] == cfg["scintillator"]["fpga"]) &
        (stream_df["TDC_CHANNEL"] == cfg["scintillator"]["tdc_ch"])]

    # create a T0 column (in ns)
    trigger_df["T0_NS"] = (trigger_df["BX_COUNTER"] + trigger_df["TDC_MEAS"] / 30) * DU
RATION_BX
    # select only hits in the same orbit of a scint trigger signal
    hits_df_ = pd.merge(
        hits_df, trigger_df[["ORBIT_CNT","T0_NS"]],
        left_on="ORBIT_CNT", right_on="ORBIT_CNT",
        suffixes=(None, None)
    )

    del trigger_df
    del hits_df
    # print the number of valid hits found in data
    print(f"Valid hits: {hits_df_.shape[0]}")

    del stream_df
    # create mapping with the loaded configurations
    mapper = Mapping(cfg)

    return computeEvents(hits_df_)
```

```python
#reading df from file
    dtype_dict = { 'HEAD':np.uint8, 'FPGA':np.uint8, 'TDC_CHANNEL':np.uint8,
                   'ORBIT_CNT':np.uint64, 'BX_COUNTER':np.uint16, 'TDC_MEAS':np.uint8 }
    print("Reading dataset from file...")
    stream_df = pd.read_csv(df_fname, dtype=dtype_dict)
    #drop NaN
    stream_df.dropna(inplace=True)
```

Not Optimized*:

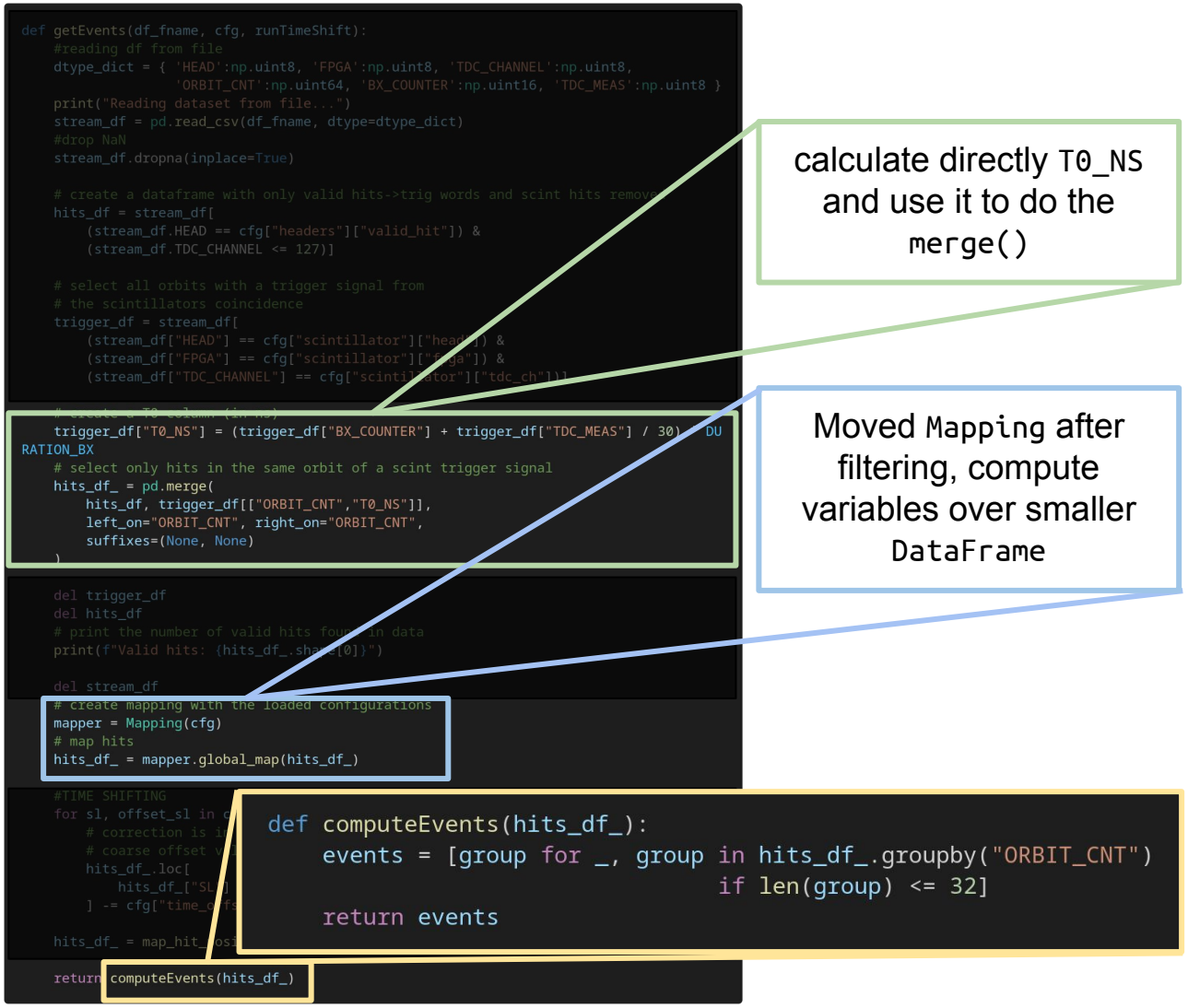
- RAM: 327 MB
- Time: 1 s

Optimized*:

- RAM: 123 MB
- Time: 0.09 s

*On ⅓ of 000054 dataset

EventsFactory.py *optimized*



calculate directly `T0_NS` and use it to do the `merge()`

Moved `Mapping` after filtering, compute variables over smaller `DataFrame`

Not Optimized*:

- RAM: 486 MB
- Time: 7.9 s

Optimized*:

- RAM: 252 MB
- Time: 0.7 s

*On ⅓ of 000054 dataset

reco.py *not optimized*

compute()

```
def compute(df):

    comb = []
    if len(df.LAYER.unique()) == 3:
        comb.append(df)
        tot_Hits = 3
    else:
        for index in list(combinations(df.index, 4)):
            tmp_df = df.loc[index, :]
            if len(tmp_df.LAYER.unique()) == 4:
                comb.append(tmp_df)  # comb[] contains combinations of data
        tot_Hits = 4
    # saving ORBIT_CNT
    orbit = np.array(df["ORBIT_CNT"])[0]
    # saving SL
    sl = np.array(df["SL"])[0]

    flag = True
    for data in comb:
        X = np.array(pd.concat([data["X_RIGHT_GLOB"], data["X_LEFT_GLOB"]]))
        Y = np.array(pd.concat([data["WIRE_Z_GLOB"], data["WIRE_Z_GLOB"]]))
        for indexes_comb in list(combinations(range(len(X)), tot_Hits)):
            new_X = []
            new_Y = []
            for i in indexes_comb:
                new_X.append(X[i])
                new_Y.append(Y[i])

            if len(np.unique(new_Y)) == tot_Hits:
                regr_tuple = linear_reg(new_X, new_Y)
                if flag:
                    min_lambda = abs(regr_tuple["chisq_comp"])
                    xdata = new_X
                    ydata = new_Y
                    res_dict = regr_tuple
                    flag = False
                    best_comb = indexes_comb
                    best_data = data
                elif abs(regr_tuple["chisq_comp"]) < min_lambda:
                    best_comb = indexes_comb
                    min_lambda = abs(regr_tuple["chisq_comp"])
                    xdata = new_X
                    ydata = new_Y
                    res_dict = regr_tuple
                    best_data = data

    big_df = pd.concat([best_data, best_data], axis=0, ignore_index=True)
    reco_df = big_df.loc[best_comb, :]
    reco_df["m"] = np.full(len(reco_df), res_dict["m"])
    reco_df["q"] = np.full(len(reco_df), res_dict["q"])
    reco_df["X"] = xdata
    res_dict["ORBIT_CNT"] = orbit
    res_dict["SL"] = sl
    return res_dict, xdata, ydata, reco_df
```

new array created at each iteration

too long code, can be reduced

useless `DataFrame` created

reco.py *optimized*

compute()

```python
def compute(df):

    comb = []
    if len(df.LAYER.unique()) == 3:
        comb.append(df)
        tot_Hits = 3
    else:
        for index in list(combinations(df.index, 4)):
            if len(df.loc[index, :].LAYER.unique()) == 4:
                comb.append(df.loc[index, :])
        tot_Hits = 4

    min_lambda = np.finfo(float).max

    for data in comb:
        X = np.array(pd.concat([data["X_RIGHT_GLOB"], data["X_LEFT_GLOB"]]))
        Y = np.array(pd.concat([data["WIRE_Z_GLOB"], data["WIRE_Z_GLOB"]]))
        for indexes_comb in list(combinations(range(len(X)), tot_Hits)):
            indexes_comb = list(indexes_comb)
            if len(np.unique(Y[indexes_comb])) == tot_Hits:
                regr_dict = linear_reg(X[indexes_comb], Y[indexes_comb])
                if abs(regr_dict["chisq_comp"]) < min_lambda:
                    min_lambda = abs(regr_dict["chisq_comp"])
                    xdata = X[indexes_comb]
                    res_dict = regr_dict
                    best_comb = indexes_comb
                    best_data = data

    reco_df = pd.concat([best_data, best_data], axis=0, ignore_index=True)
    reco_df = reco_df.loc[best_comb, :]
    reco_df["m"] = np.full(len(reco_df), res_dict["m"])
    reco_df["q"] = np.full(len(reco_df), res_dict["q"])
    reco_df["X"] = xdata
    if xdata is None: return

    return reco_df
```

used slicing instead of creating new array

reduced code

no more useless `DataFrame`

Not Optimized*:

- RAM: 0.09 MB
- Time: 0.04 s

Optimized*:

- RAM: 0.08 MB
- Time: 0.04 s

*On a single event `DataFrame`

reco.py
getRecoResults()

Not Optimized:

```
def getRecoResults(events):
    resultsDf = []

    for df_E in events:
        event_reco_df = computeEvent(df_E)
        if event_reco_df is None:
            continue
        if len(event_reco_df)==0:
            continue
        resultsDf.append(event_reco_df)

    return resultsDf
```

each reconstruction on a single event `DataFrame` launched on the same process, only one CPU core used

Not Optimized*:

- RAM: 35 MB
- Time: 436 s

Optimized:

```
def getRecoResults_mp(events):

    pool = Pool(processes=cpu_count()-2)

    result = pool.map_async(computeEvent, events)
    resultsDf = result.get()
    pool.close()
    pool.join()
    resultsDf = [x for x in resultsDf if x is not None]

    return resultsDf
```

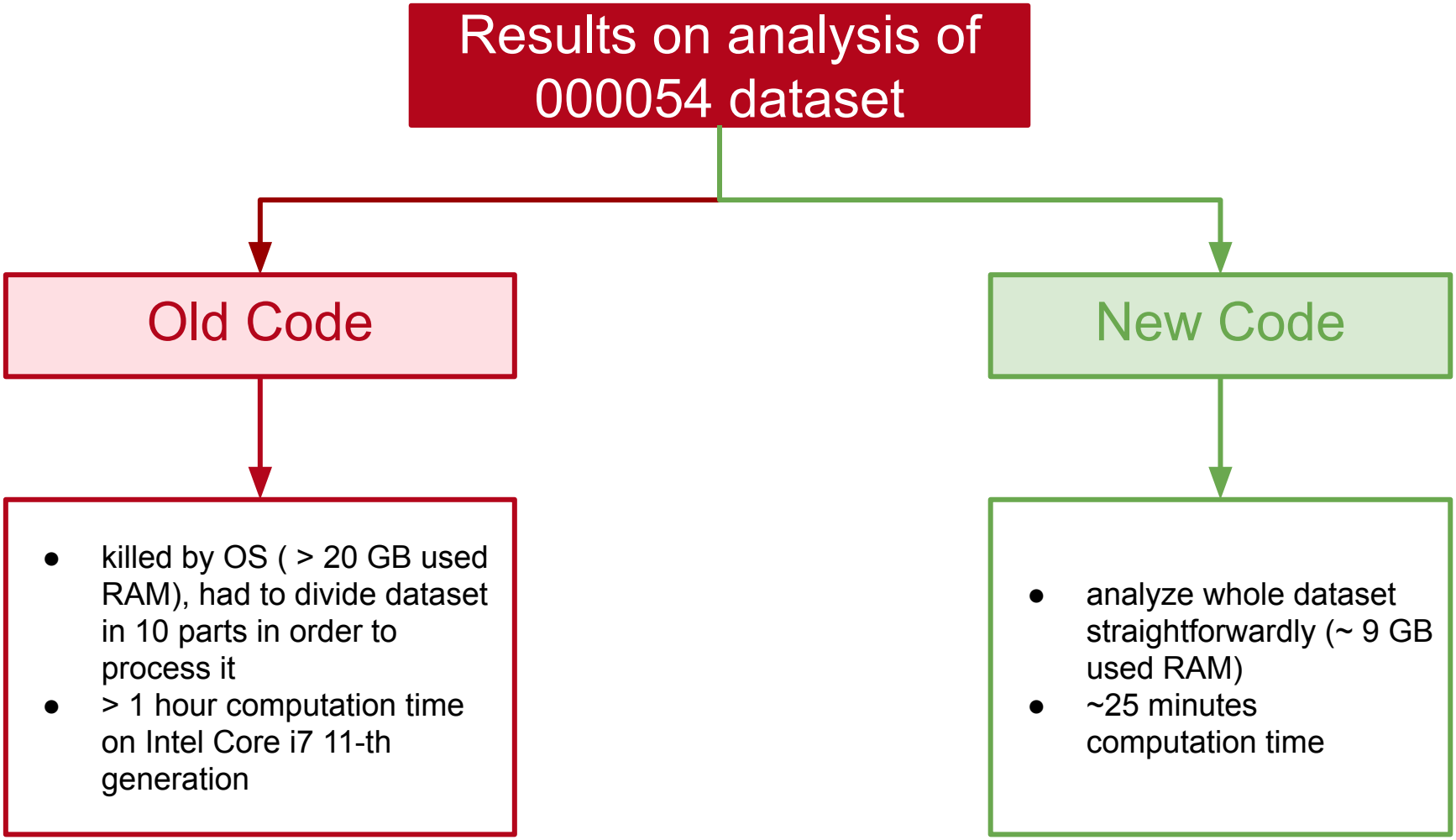
more CPU cores are used in order to reconstruct the event through `multiprocessing` library

Optimized*:

- RAM: 25 MB
- Time: 157 s

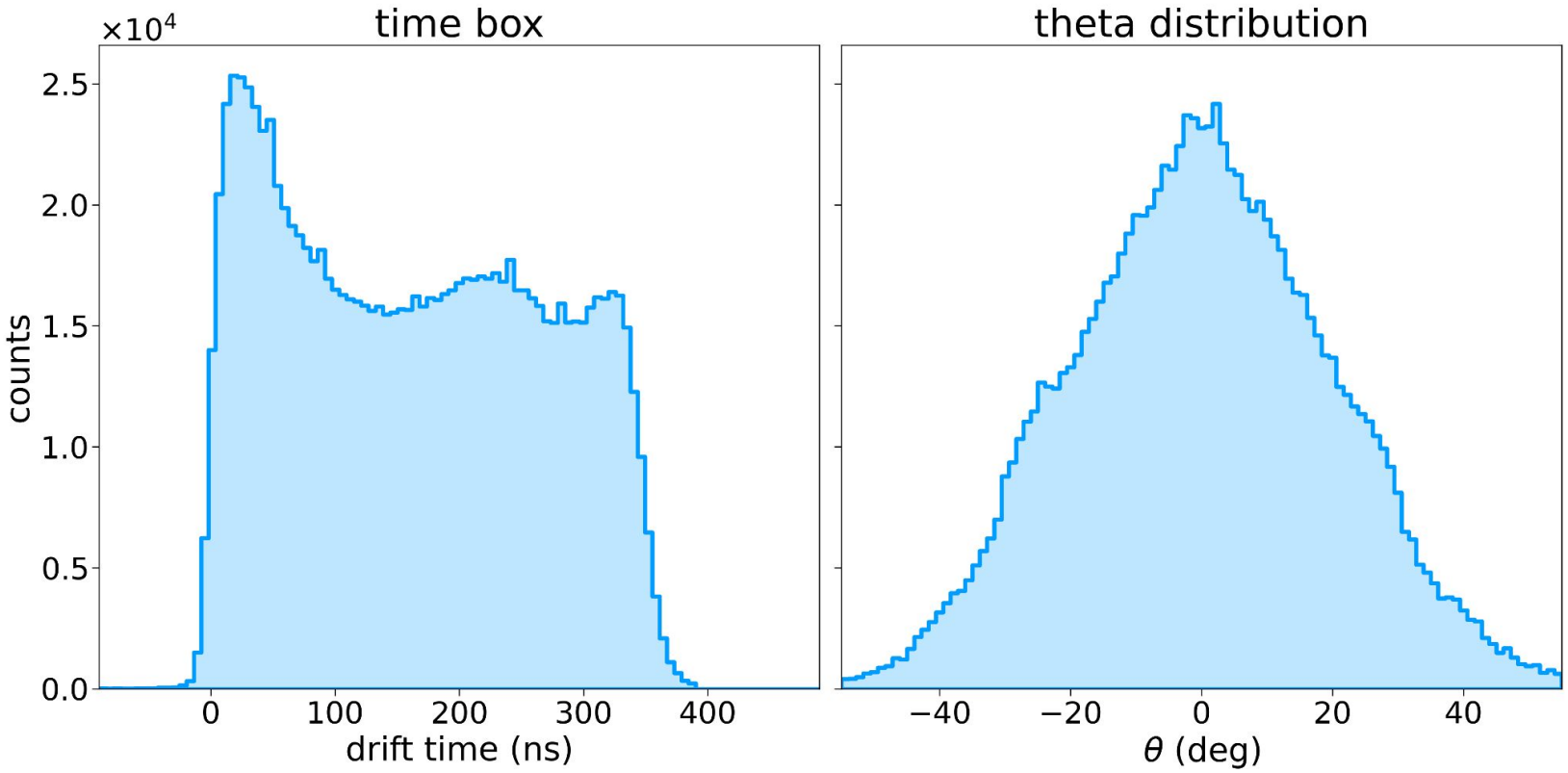
*On ⅓ of 000054 dataset

Results

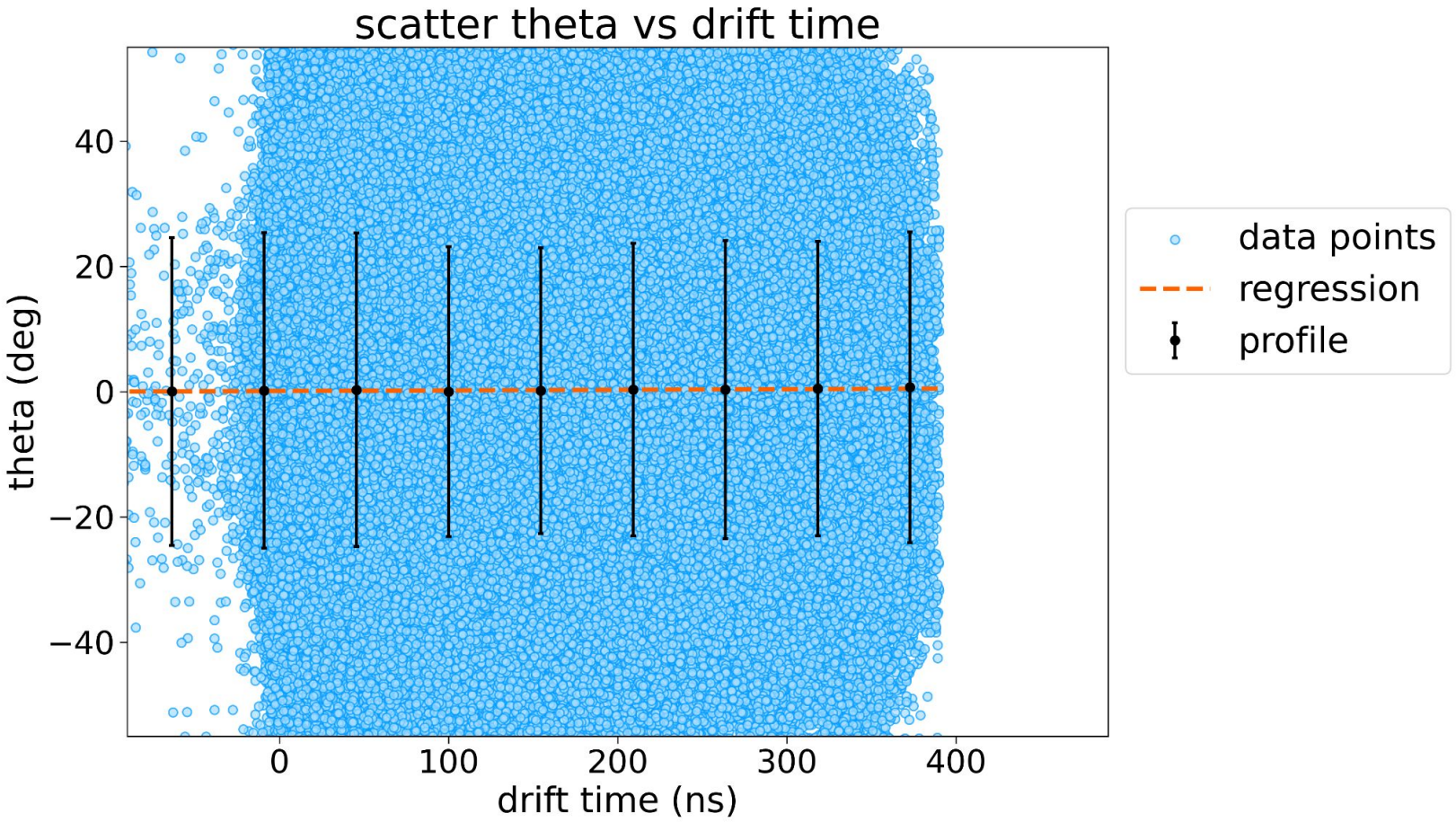

Results on analysis of 000054 dataset
Old Code
New Code
killed by OS (> 20 GB used RAM), had to divide dataset in 10 parts in order to process it
> 1 hour computation time on Intel Core i7 11-th generation
analyze whole dataset straightforwardly (~ 9 GB used RAM)
~25 minutes computation time

θ - drift time correlation

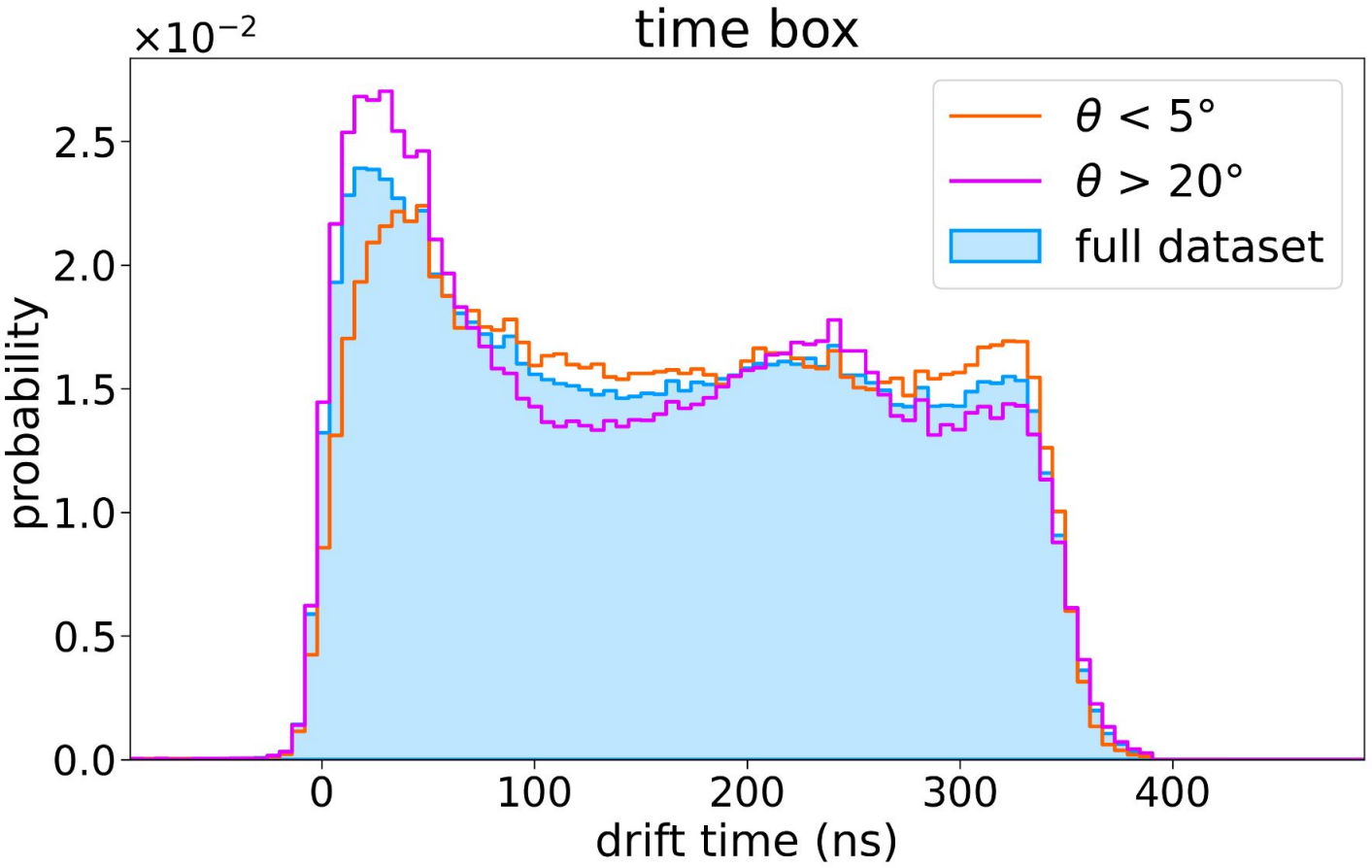
Drift Time and Theta Distribution



Data Inspection



Start cutting data



Two statistical approaches

Normalization

Probability

sum of all the heights is equal to 1

for each bin:

$$h_{\mathrm{norm},i} = \frac{h_i}{\sum_{j=0}^{n_{\mathrm{bin}}} h_j}$$

Density

total area = 1

for each bin:

$$h_{\mathrm{norm},i} = \frac{h_i}{\int h(x)dx}$$

Analysis steps

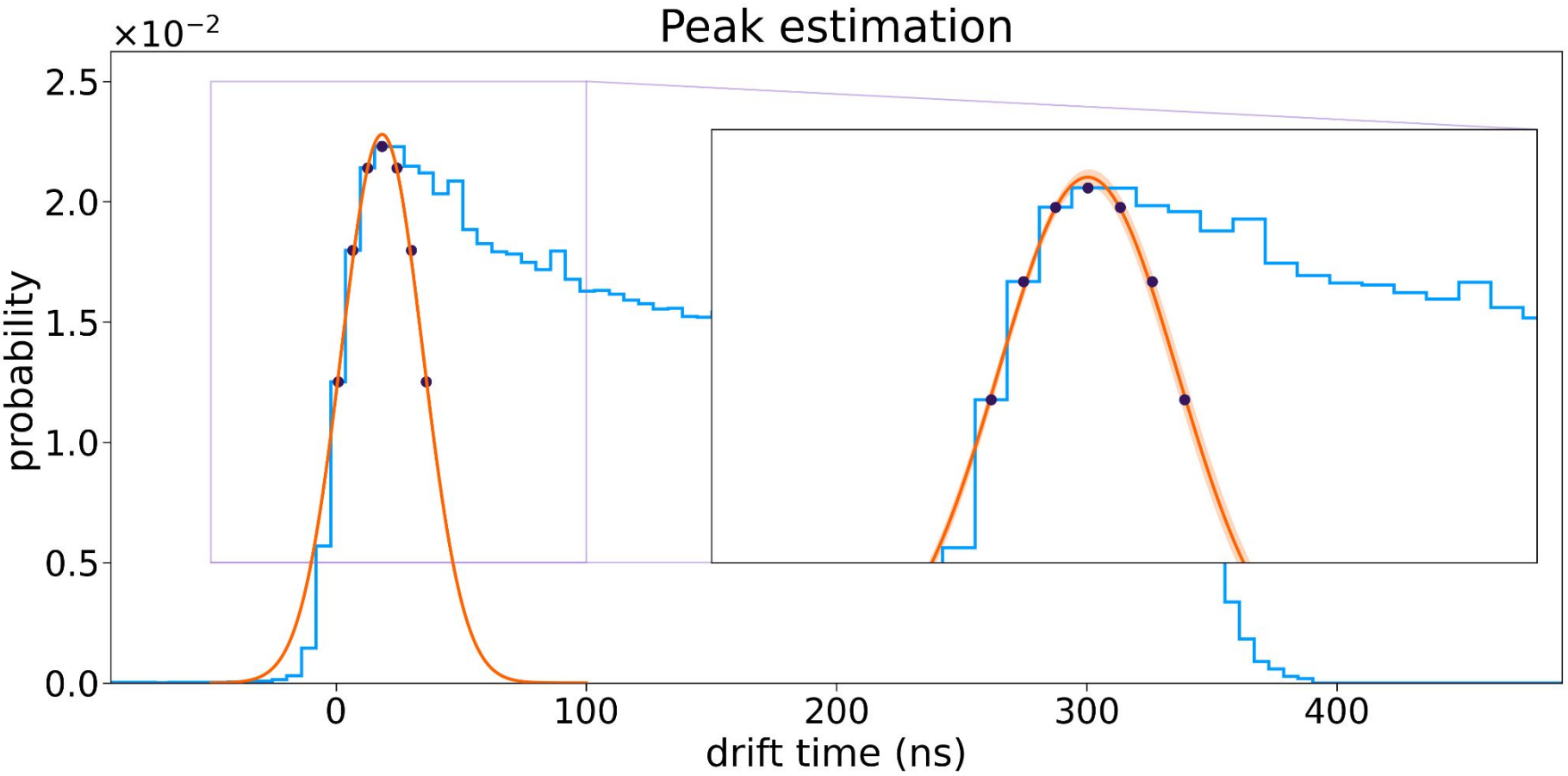
- start cutting dataset → Theta intervals

1. low cut : $\theta < \theta_i$
2. high cut : $\theta > \theta_i$
3. middle cut : $\theta_{low} < \theta < \theta_{high}$

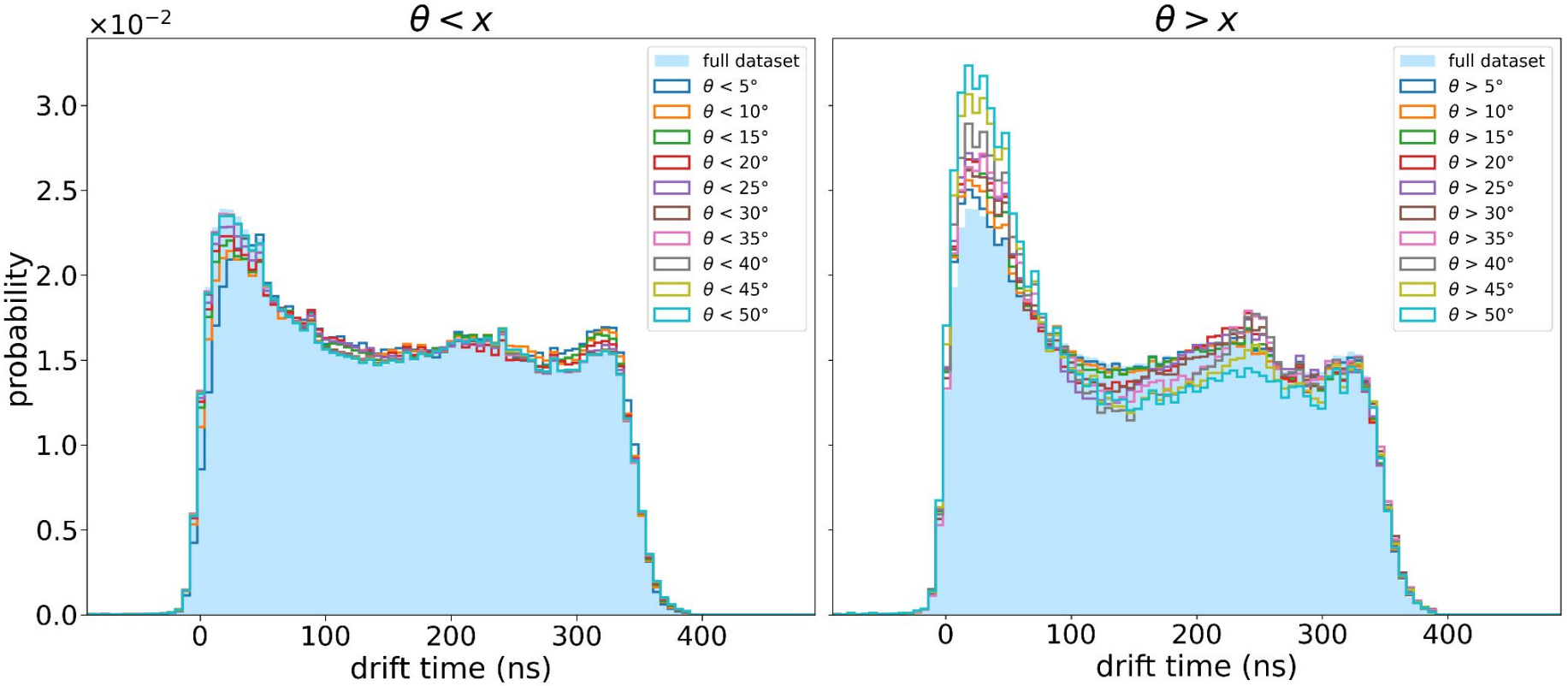
- estimate the probability of small drift time (0 ns < t < 97 ns) for each cutting approach

- To better estimate the height of the peaks → Gaussian fit

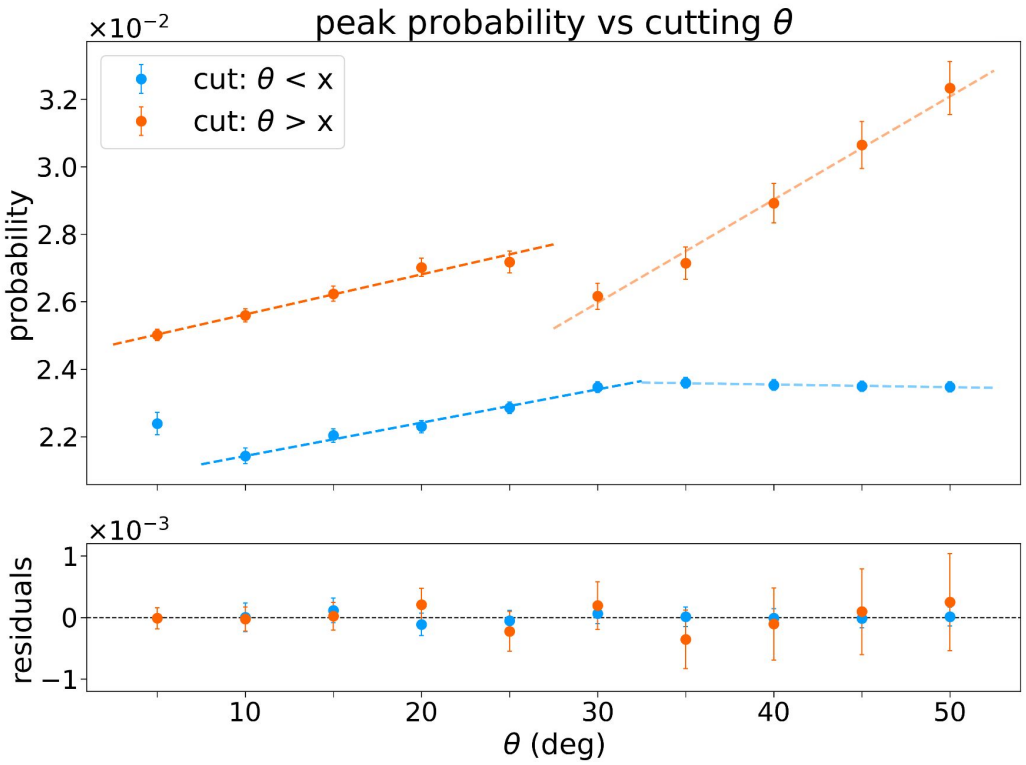
Gaussian fit



Probability: Low and high cut histograms



Probability: Low and high cut fit



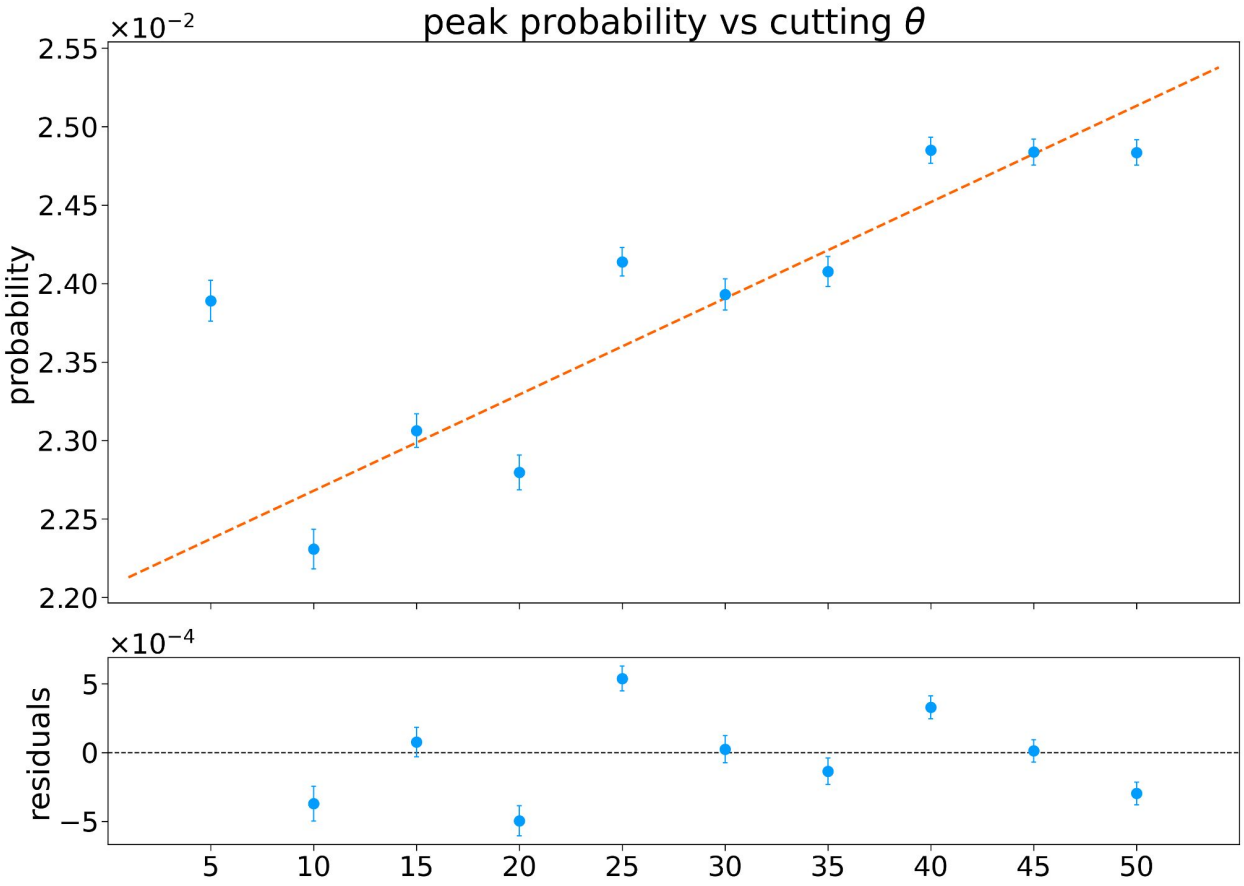
r = 0.99317
p_value = 6.77e-04
chi = 0.9843
p_value_chi = 0.805

r = 0.9530
p_value = 4.69e-02
chi = 0.0323
p_value_chi = 0.984

r = 0.98644
p_value = 1.89e-03
chi = 1.1326
p_value_chi = 0.769

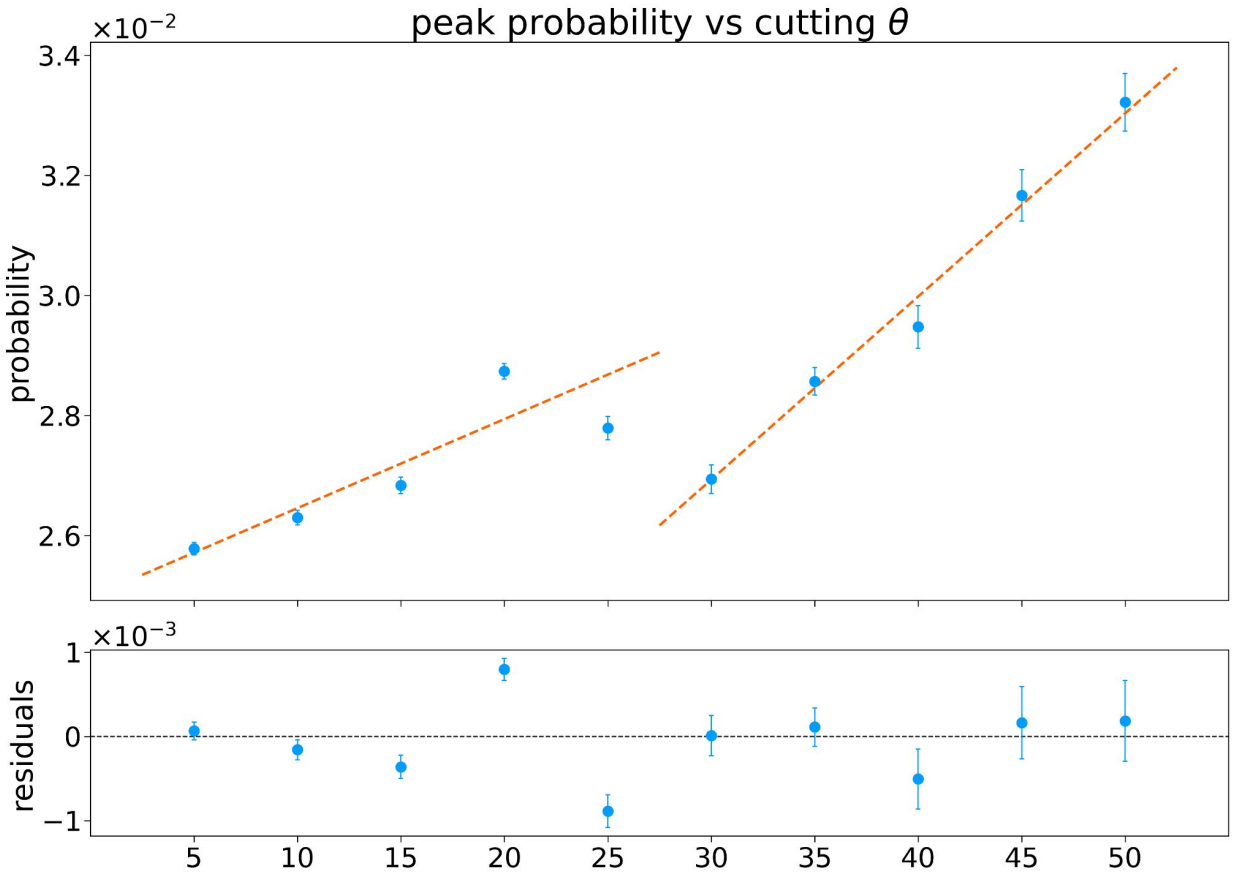
r = 0.99575
p_value = 3.32e-04
chi = 0.96601
p_value_chi = 0.809

Probability: Low cut gaussian



r = 0.93778
p_value = 1.86e-04
chi = 94.8909
p_value_chi = 1.22e-17

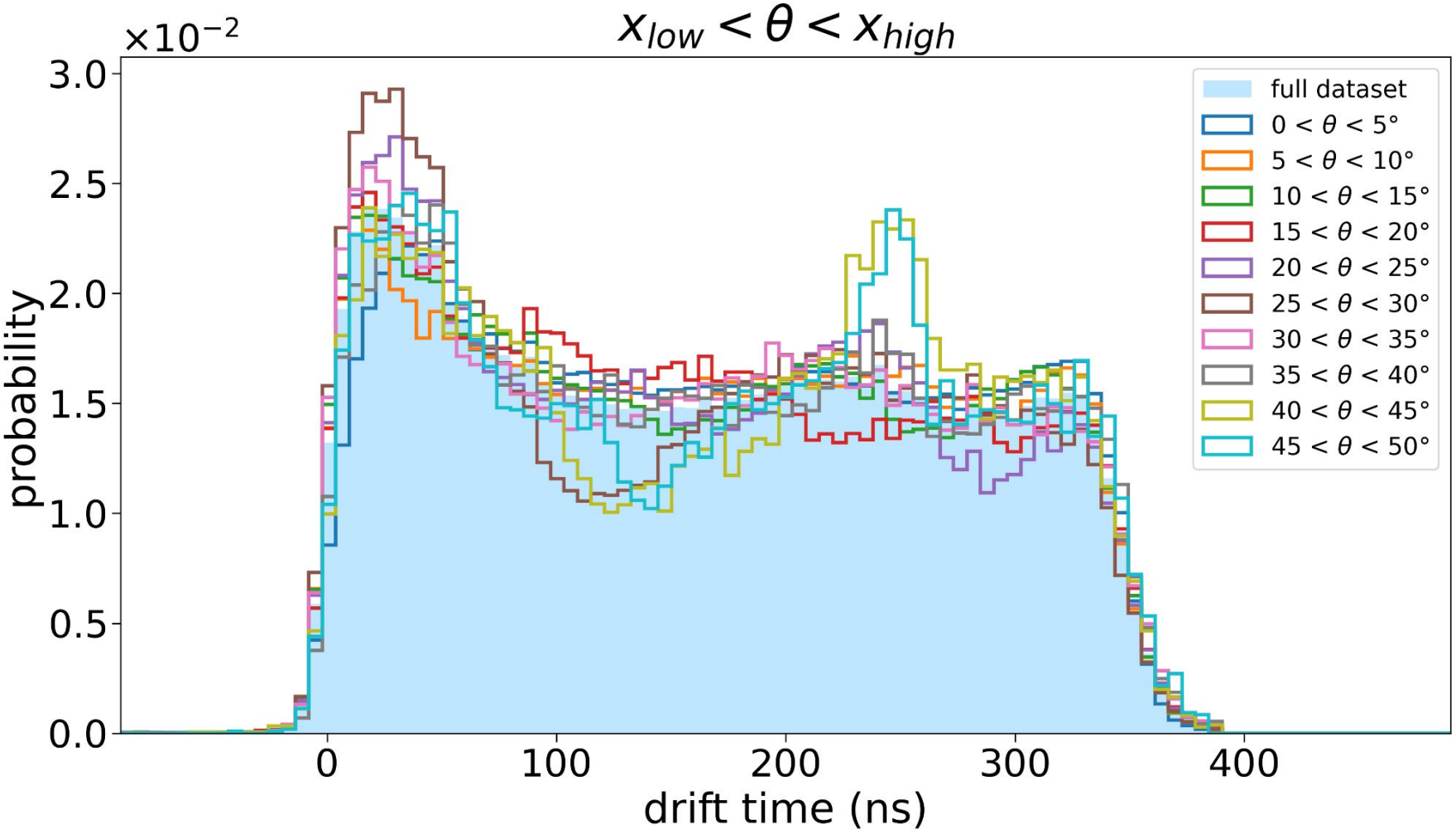
Probability: high cut gaussian



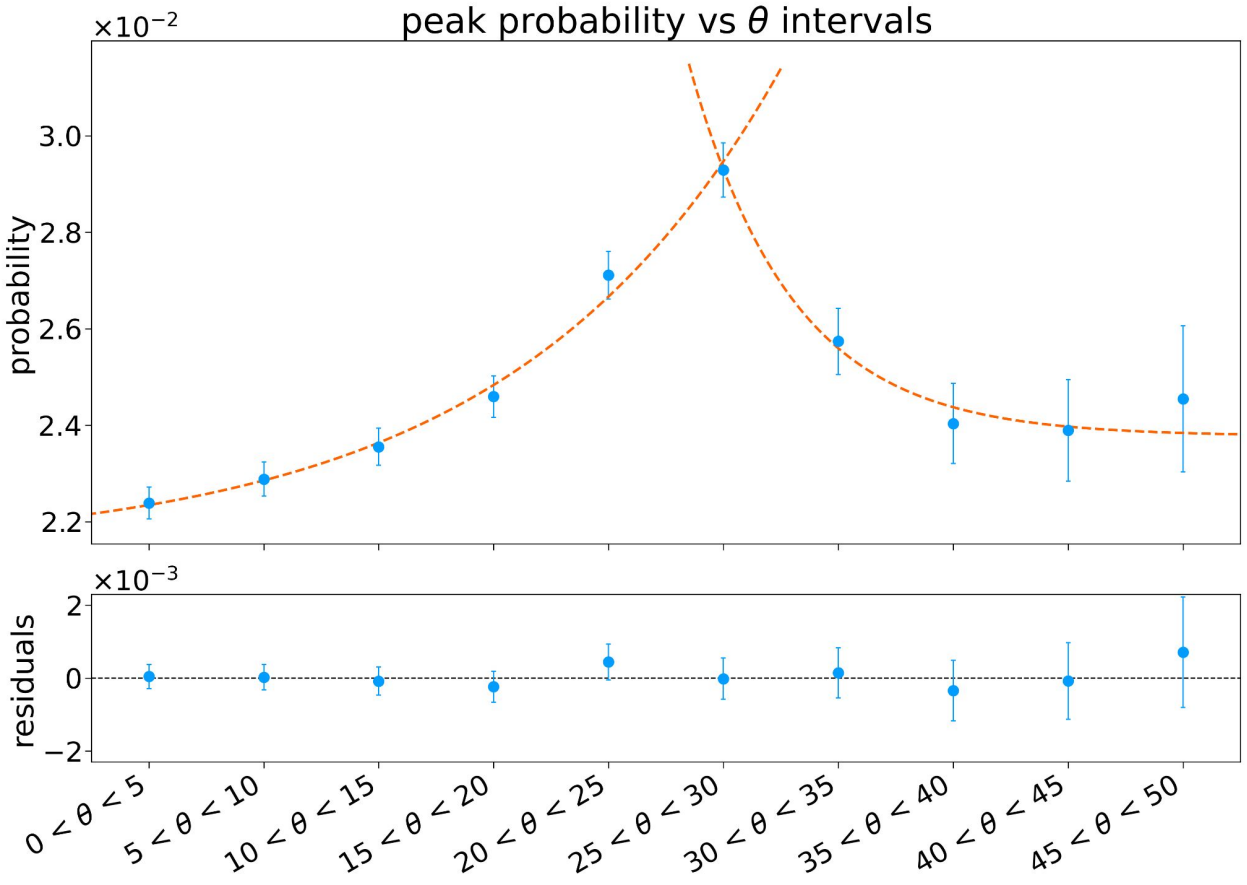
r = 0.86299
p_value = 5.96e-02
chi = 67.515
p_value_chi = 1.45e-14

r = 0.99369
p_value = 6.02e-04
chi = 2.5304
p_value_chi = 0.4698

Probability: Middle cut histograms



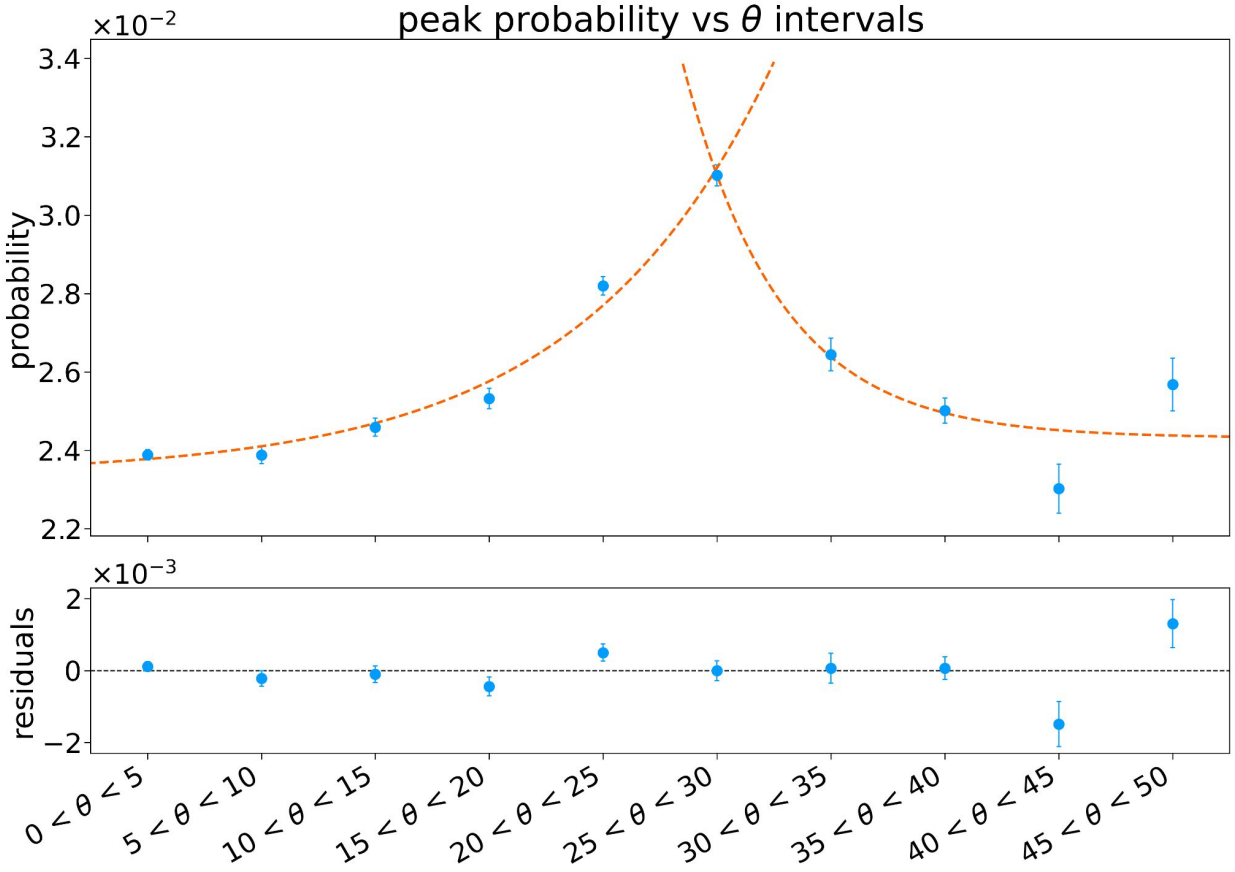
Probability: Middle cut fit



chi = 1.2911
p_value_chi = 0.7312

chi = 0.4374
p_value_chi = 0.804

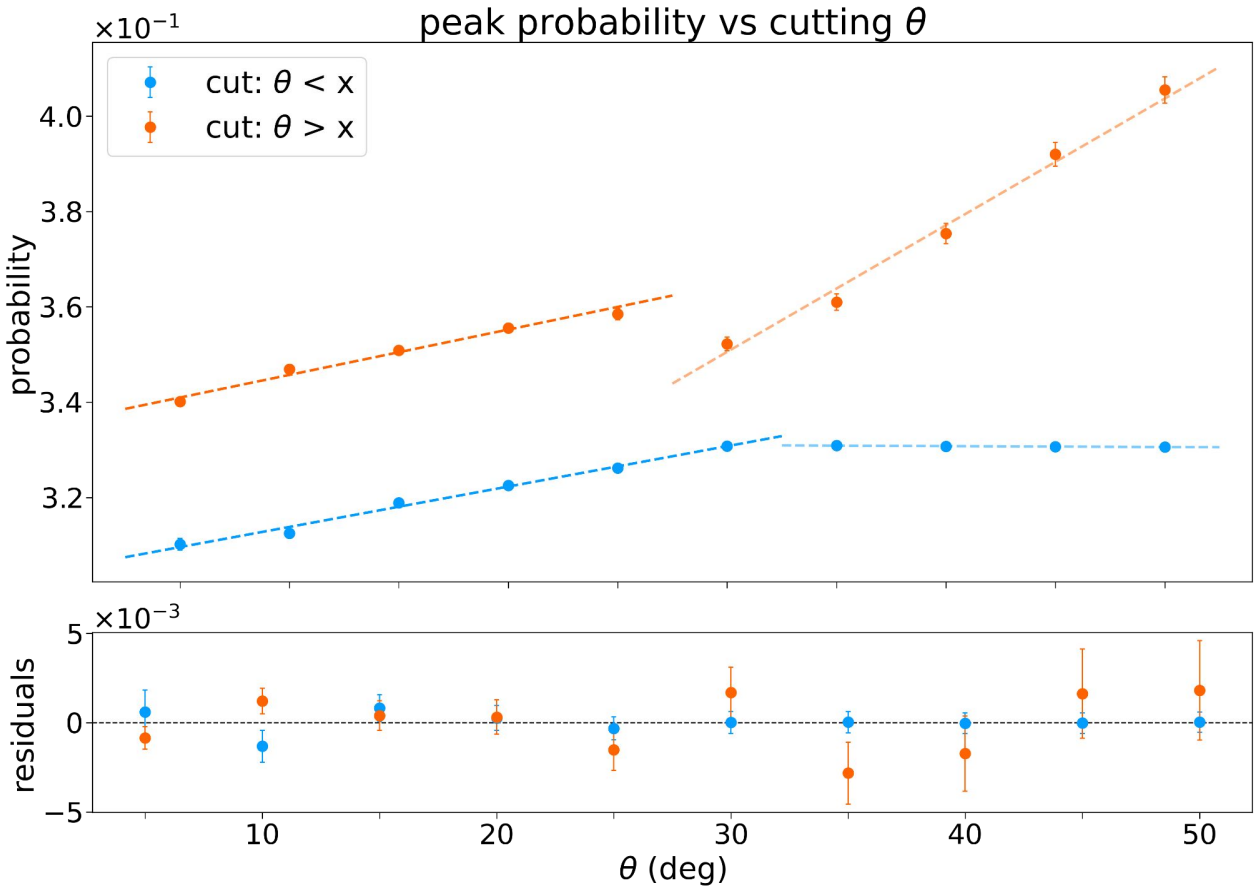
Probability: Middle cut gaussian



chi = 9.4783
p_value_chi = 0.0207

chi = 9.7592
p_value_chi = 1.453e-14

Density: Low and high cut fit



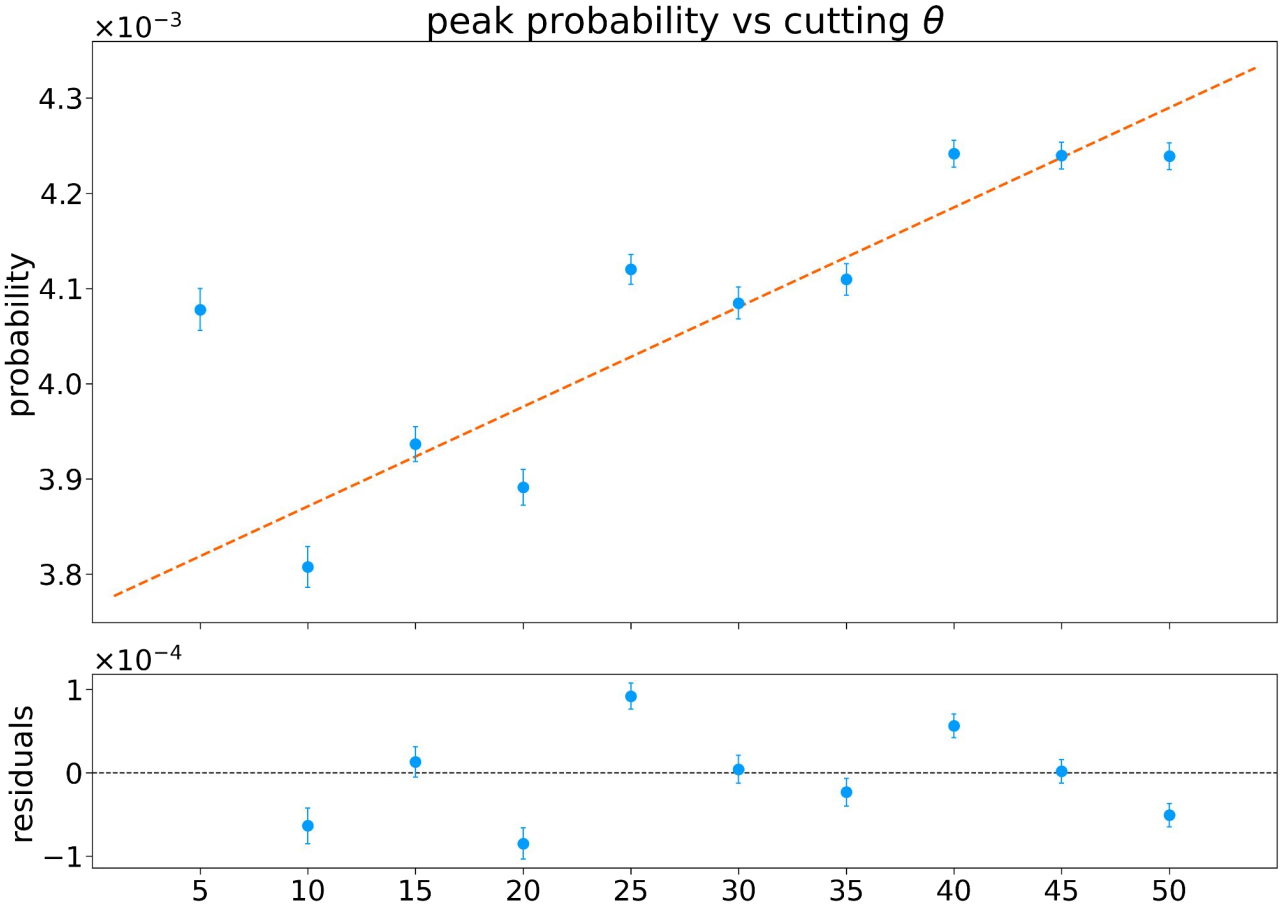
r = 0.9953
p_value = 3.27e-05
chi = 3.936
p_value_chi = 0.415

r = 0.96354
p_value = 3.65e-02
chi = 0.0108
p_value_chi = 0.995

r = 0.9898
p_value = 1.22e-03
chi = 6.7043
p_value_chi = 0.152

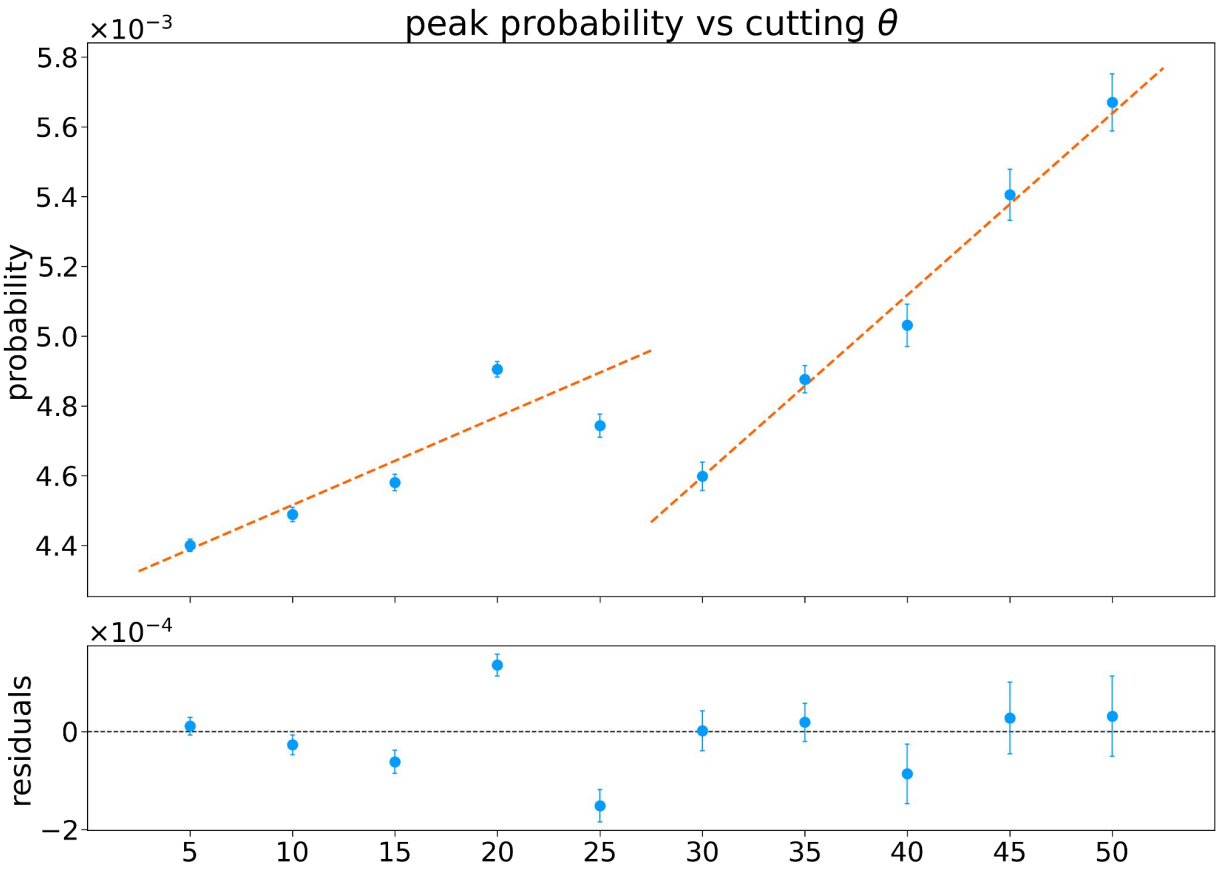
r = 0.9954
p_value = 3.72e-04
chi = 5.5726
p_value_chi = 0.134

Density: Low cut gaussian



r = 0.93778
p_value = 1.86e-04
chi = 94.886
p_value_chi = 1.223e-17

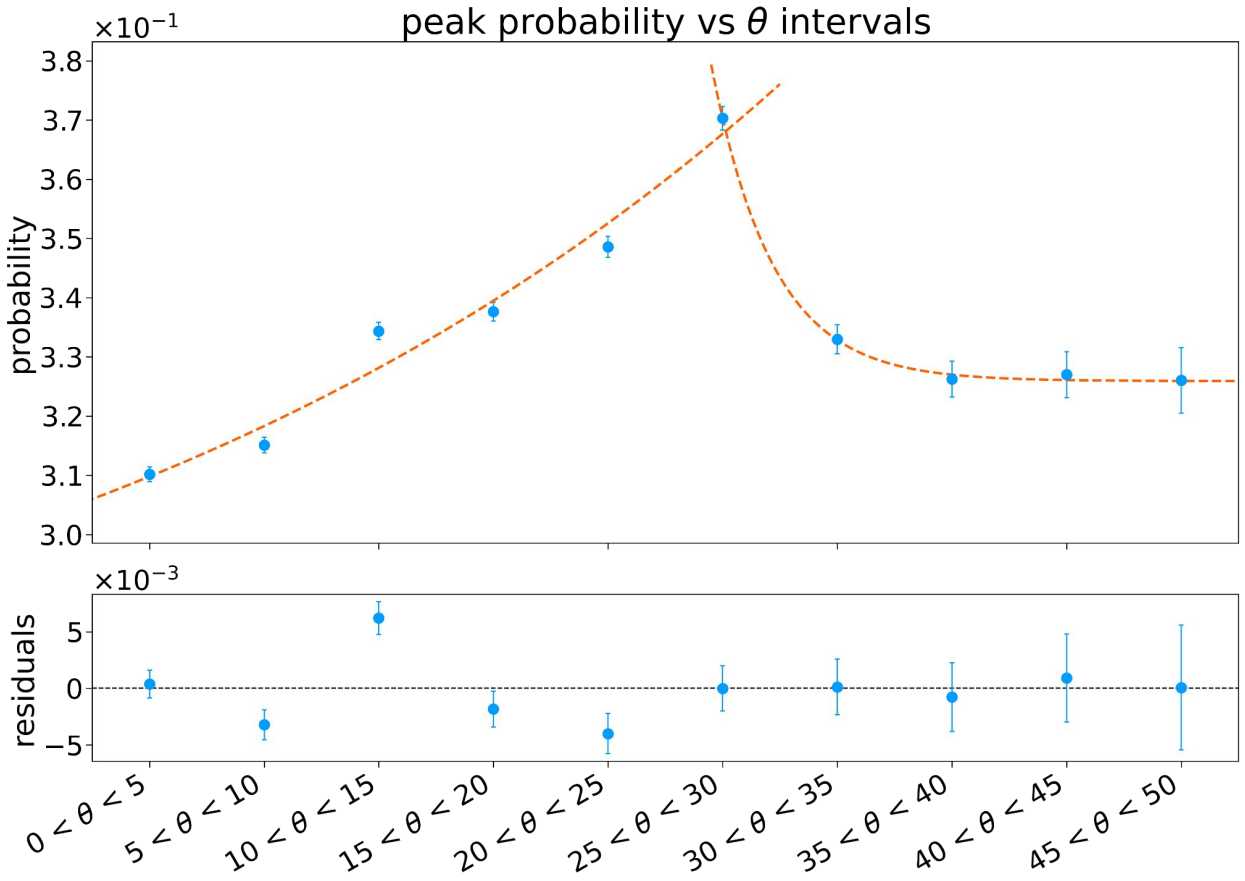
Density: Low high gaussian



r = 0.8629
p_value = 5.96e-02
chi = 67.51
p_value_chi = 1.456e-14

r = 0.99369
p_value = 6.02e-04
chi = 2.53018
p_value_chi = 0.46986

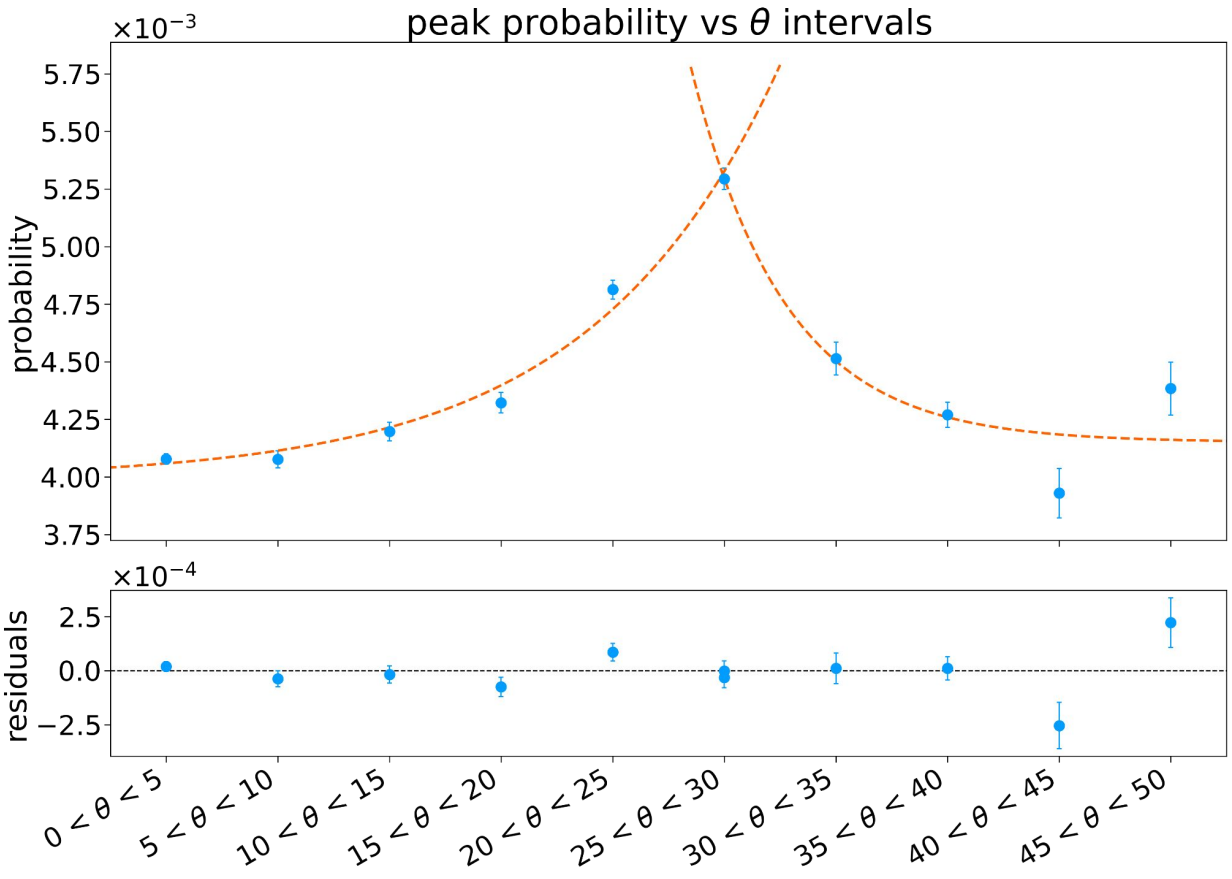
Density: Middle cut fit



chi = 32.677
p_value_chi = 3.766e-07

chi = 0.1209
p_value_chi = 0.9413

Density: Middle cut gaussian



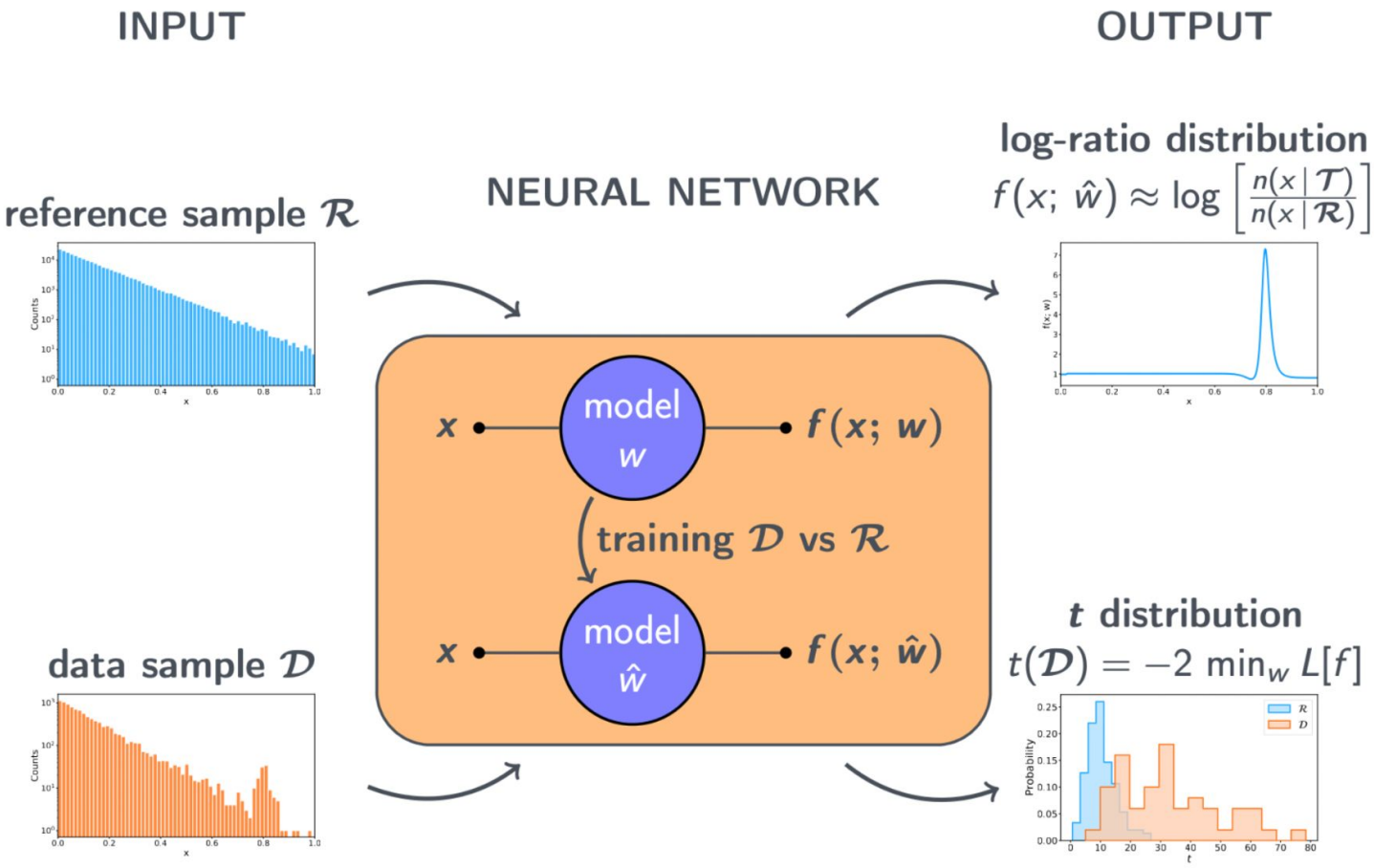
chi = 9.4778
p_value_chi = 0.0207

chi = 9.7582
p_value_chi = 1.45e-12

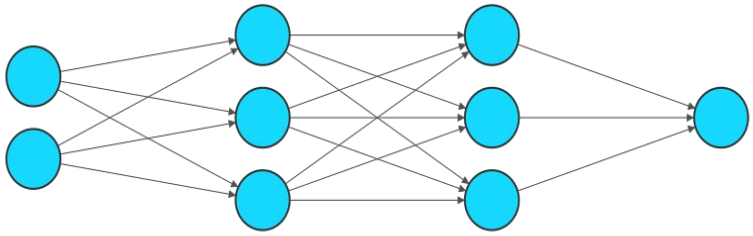
NPLM Algorithm

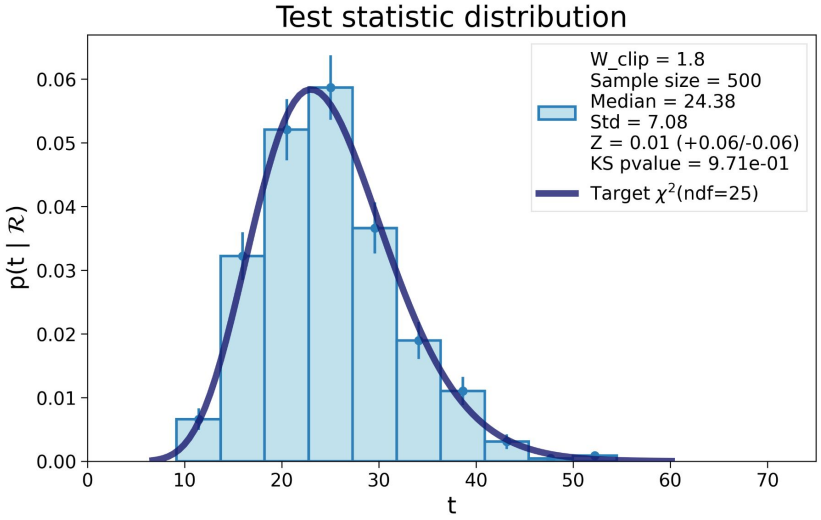
DQM performance on a 2D input dataset

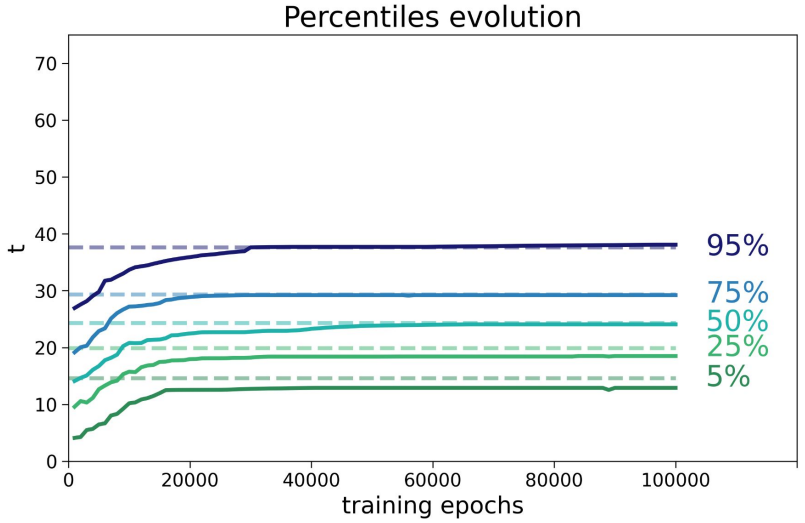
NPLM algorithm reminder



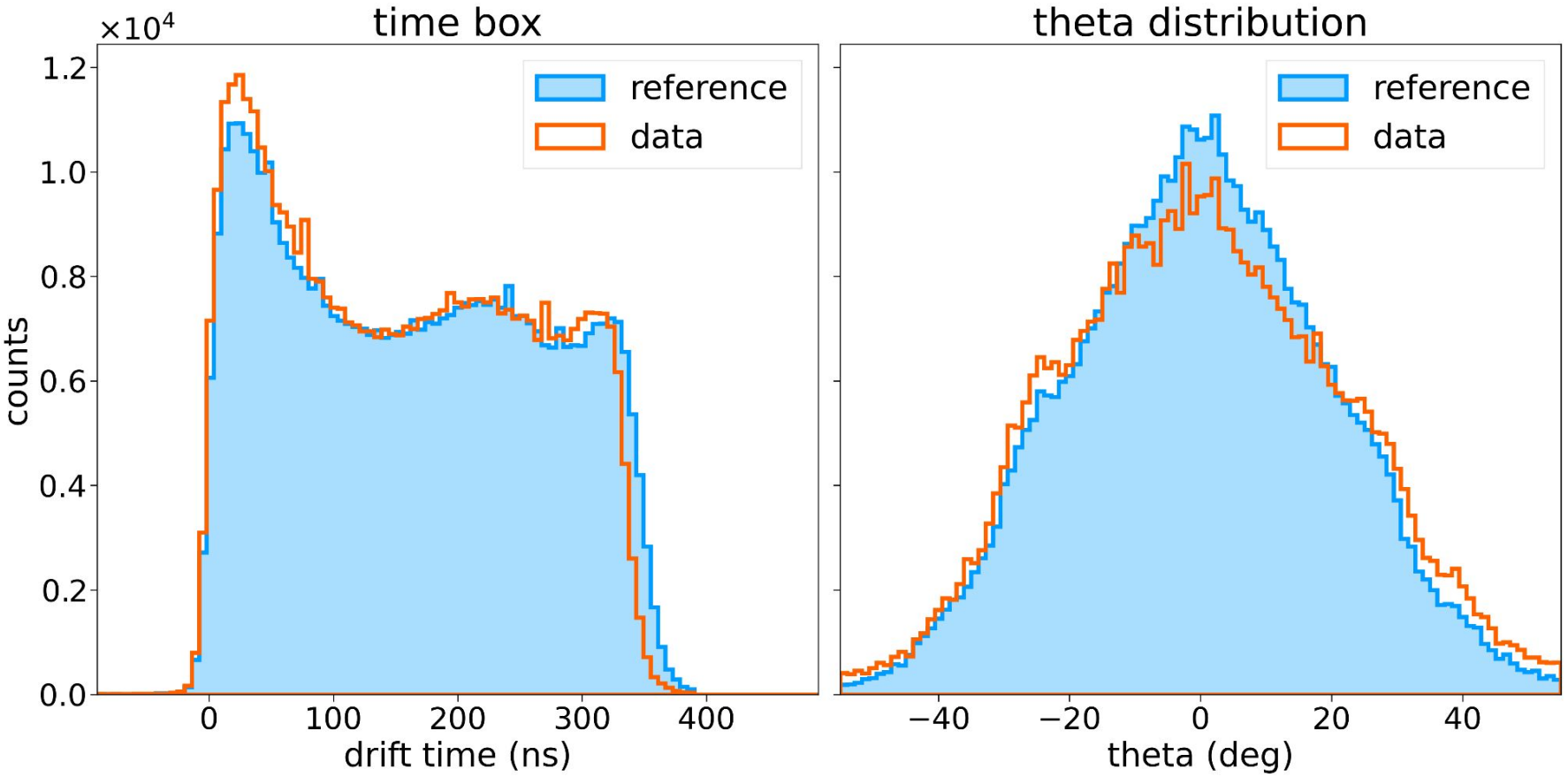
Tuning the Neural Network







Datasets: Reference and Data



NPLM output

Untouched datasets

Weight clipping = 1.8

- $N_{Reference}$ = 200’000
- N_{Data} = 10’000

NPLM output

Untouched datasets

Weight clipping = 1.8

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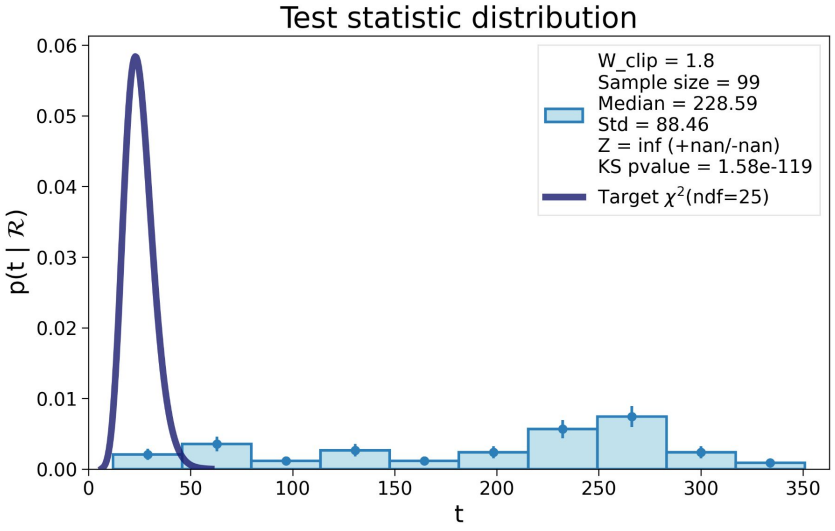

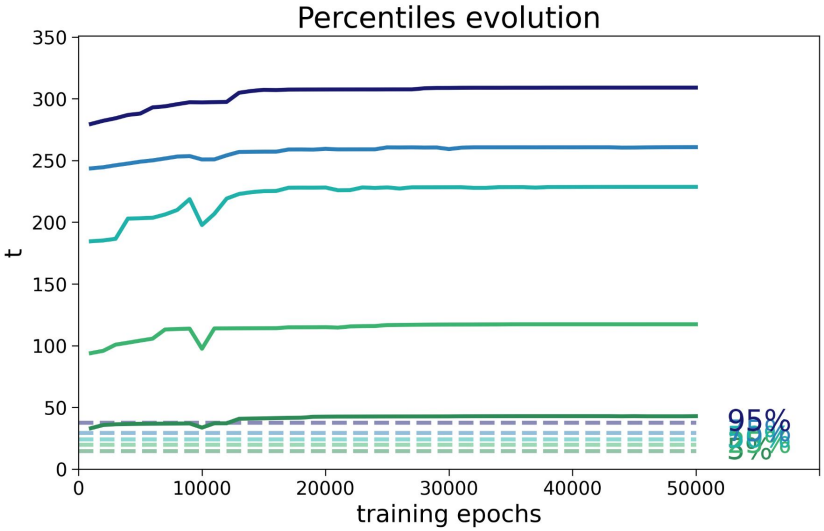

Cutting the angular feature *θ*

θ intervals considered:

- $0° \leq \theta \leq 15°$
- $0° \leq \theta \leq 45°$
- $0° \leq \theta \leq 50°$
- $5° \leq \theta \leq 45°$
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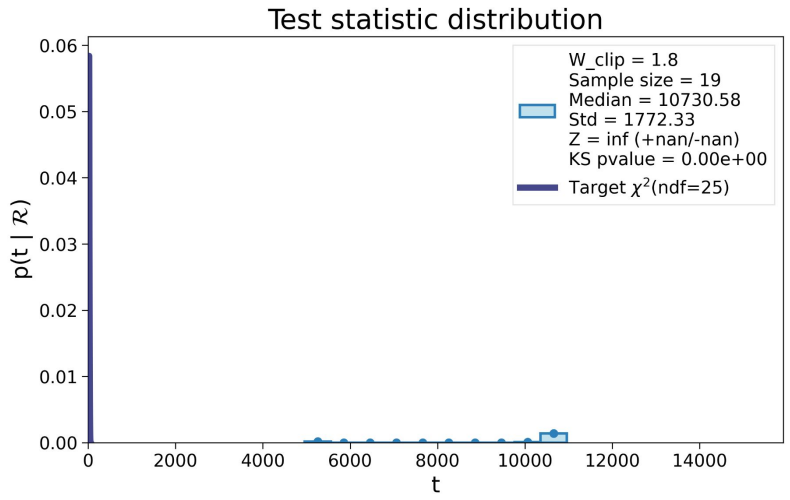

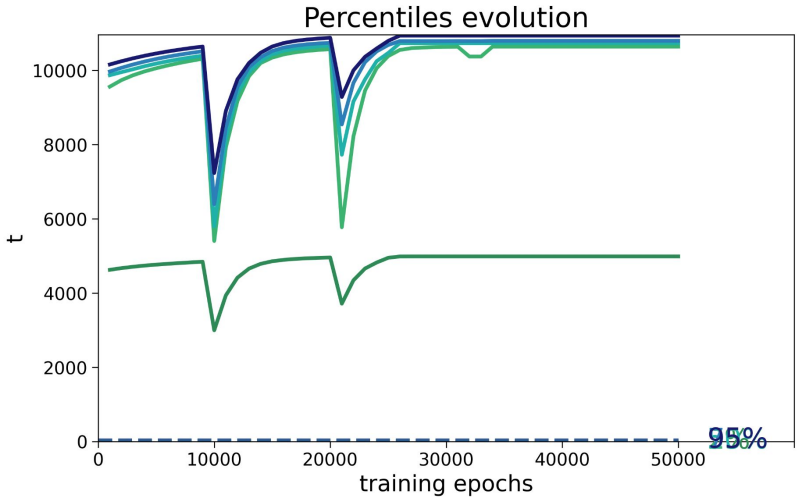

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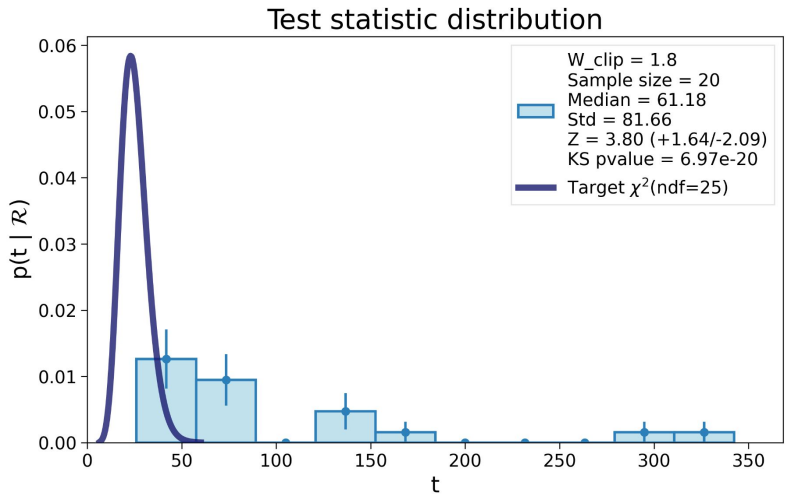

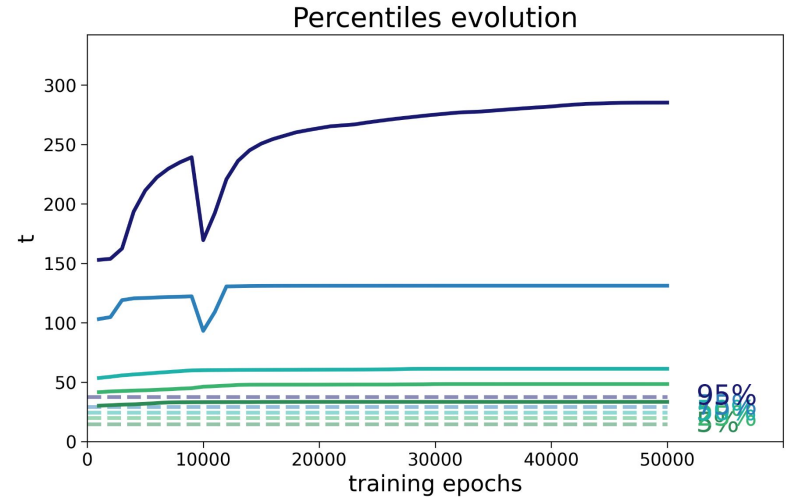

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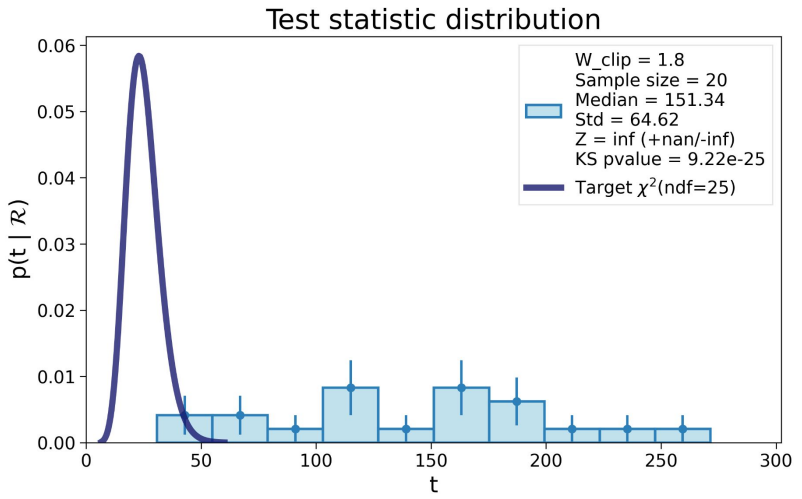

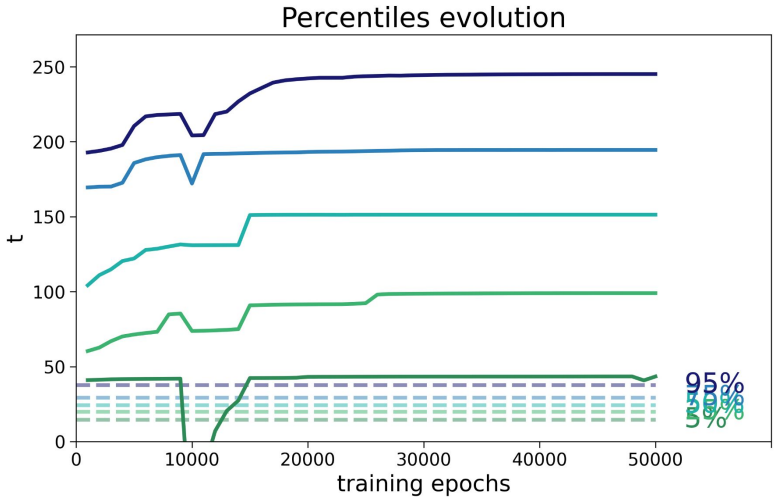

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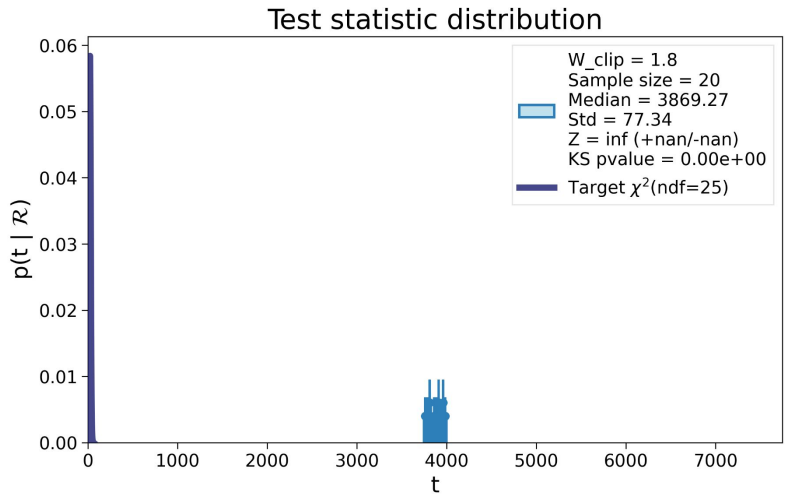

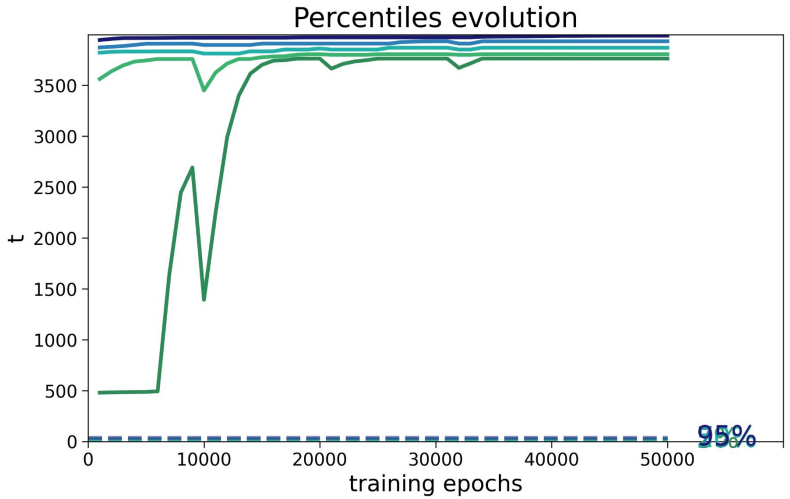

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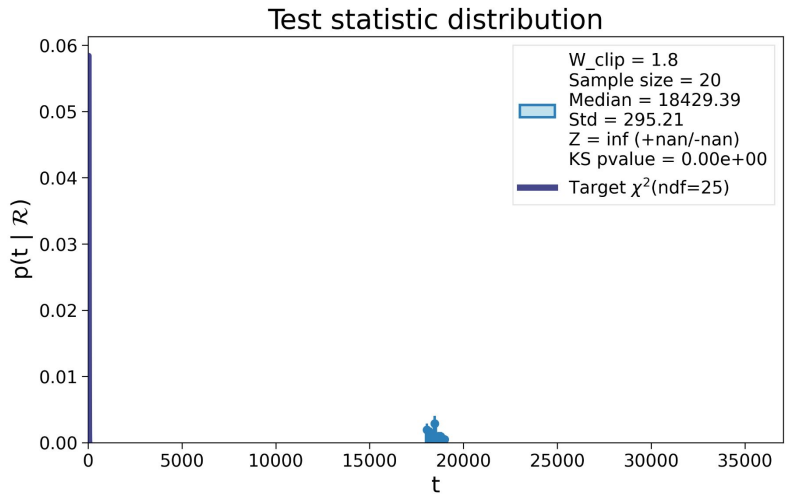

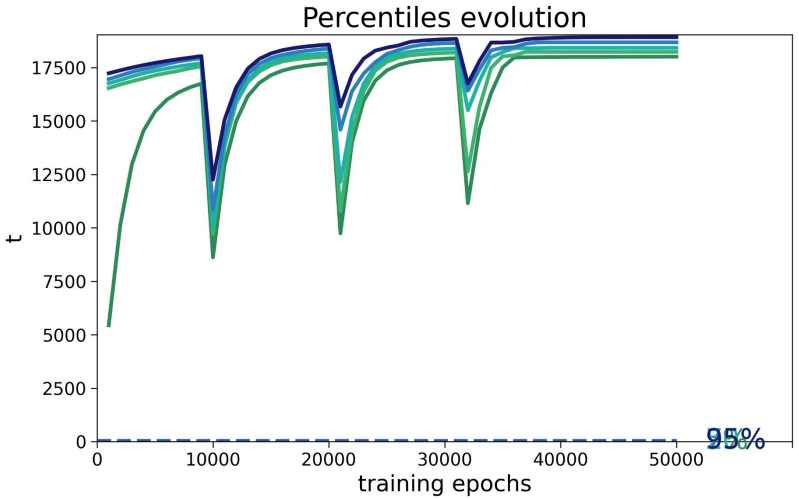

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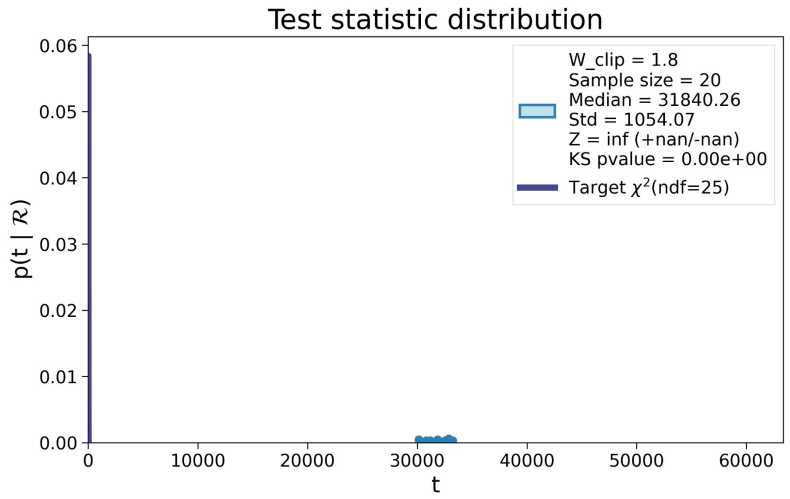
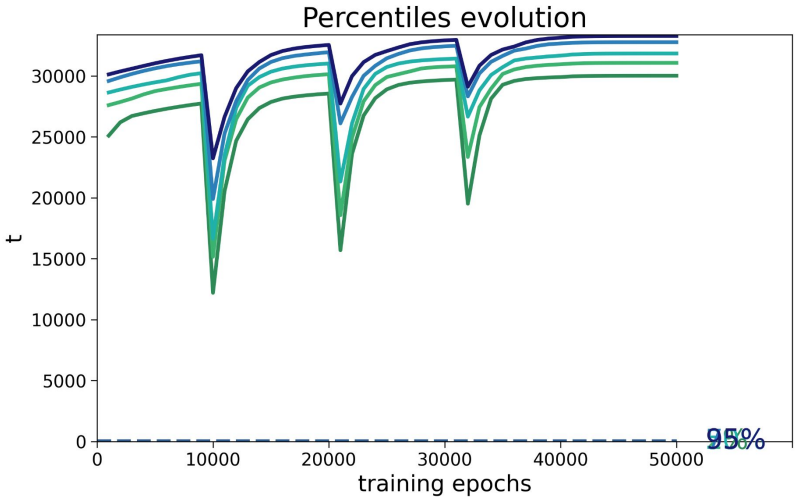
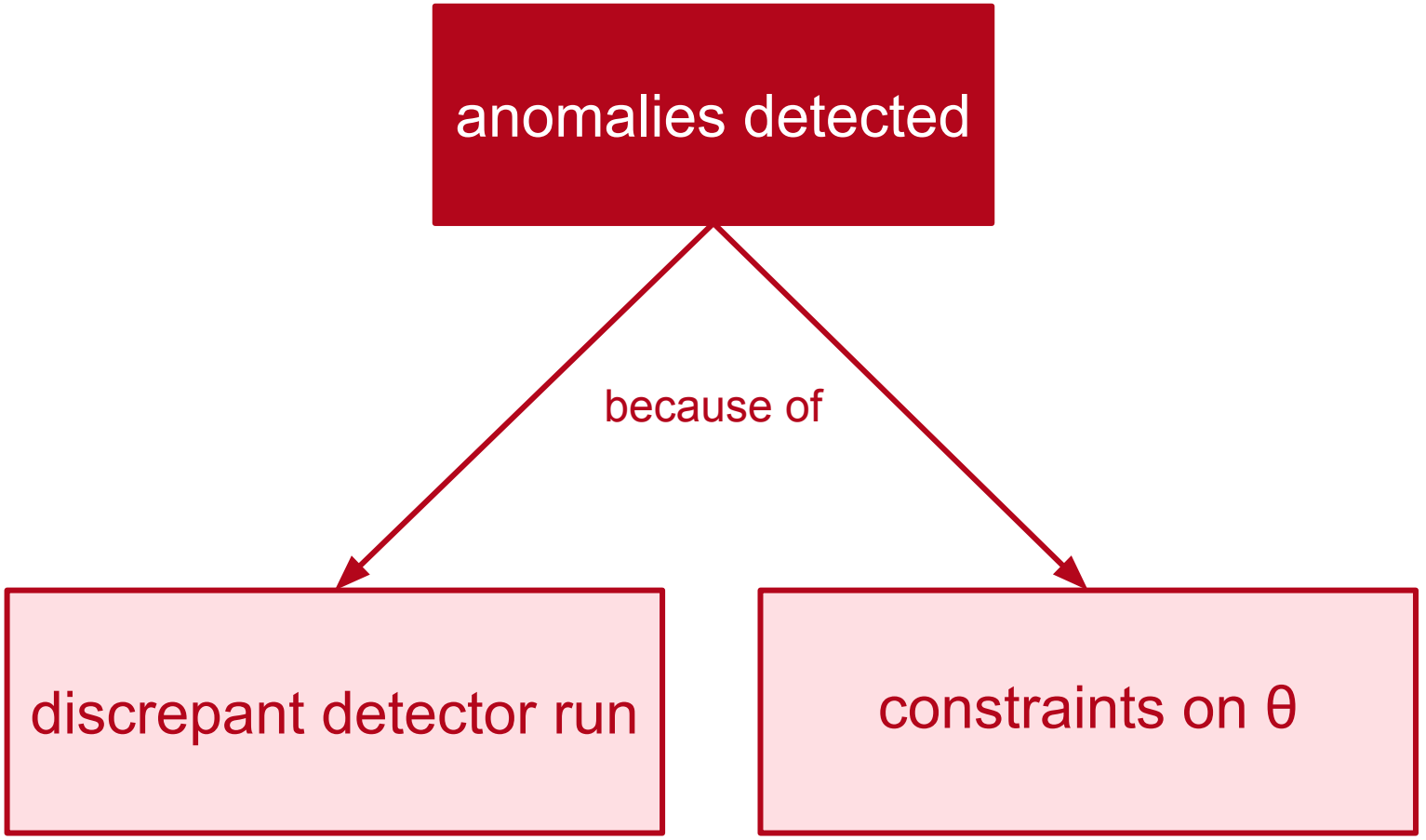




Cross-check using Reference



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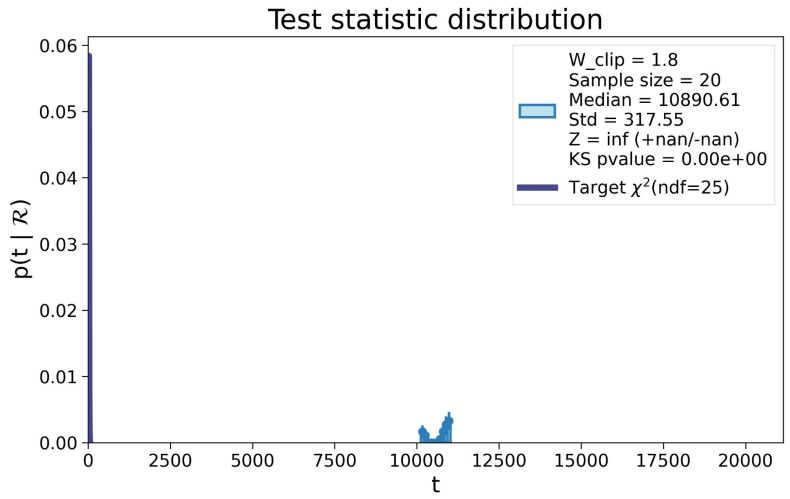

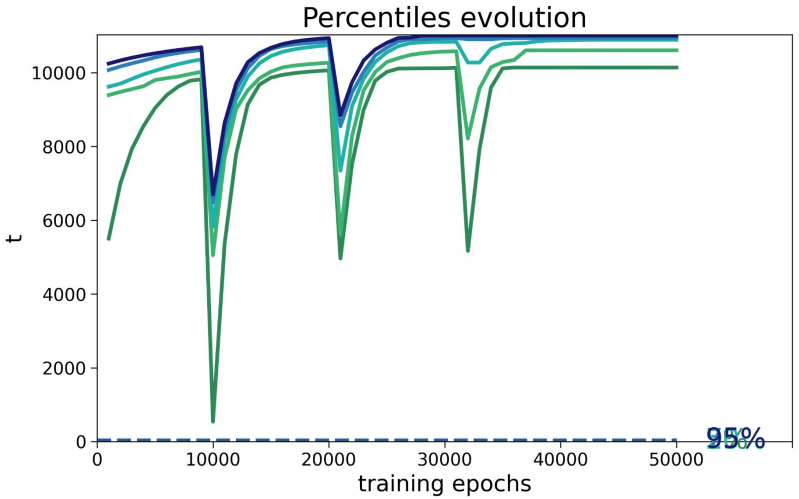

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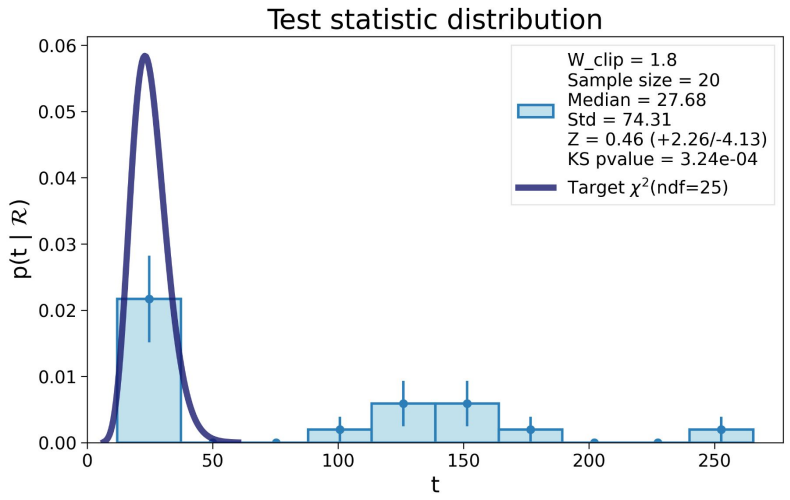

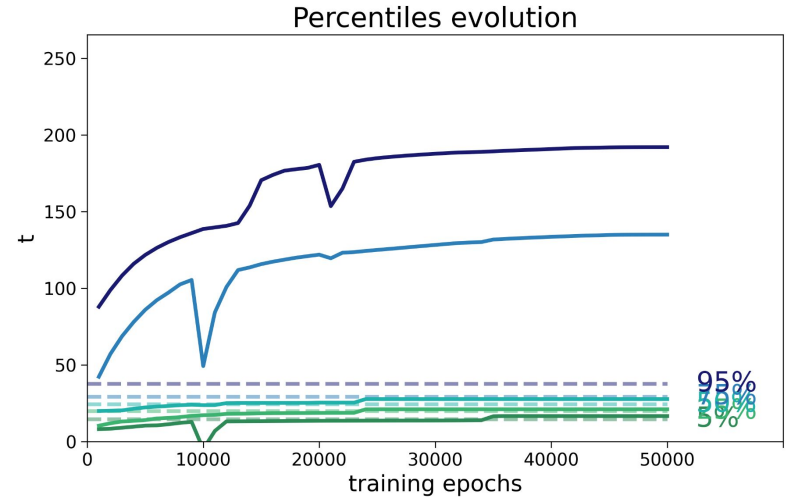

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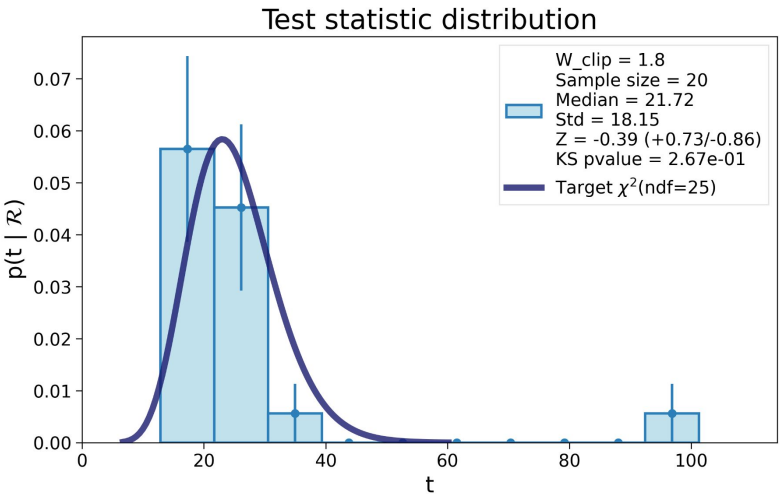

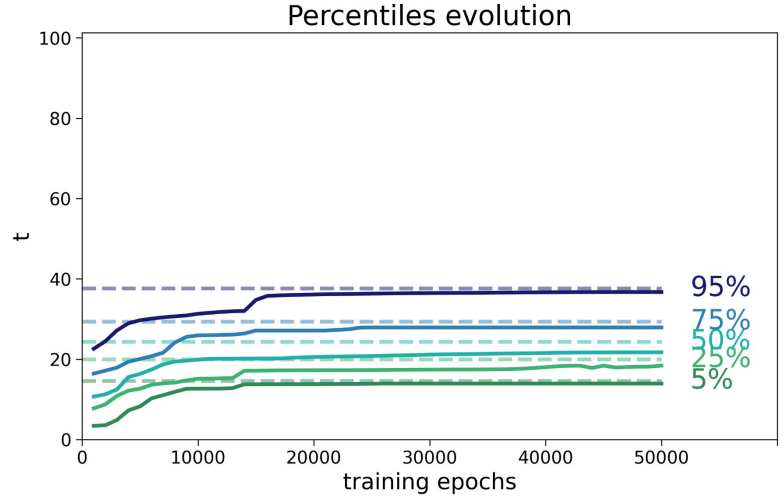

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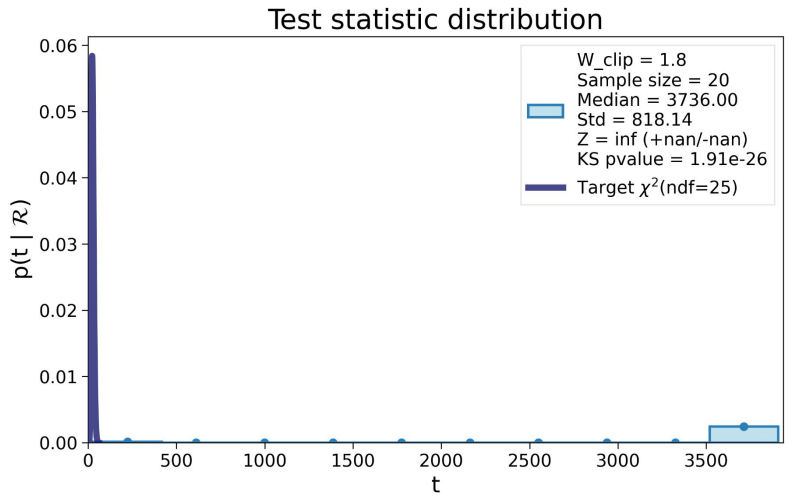

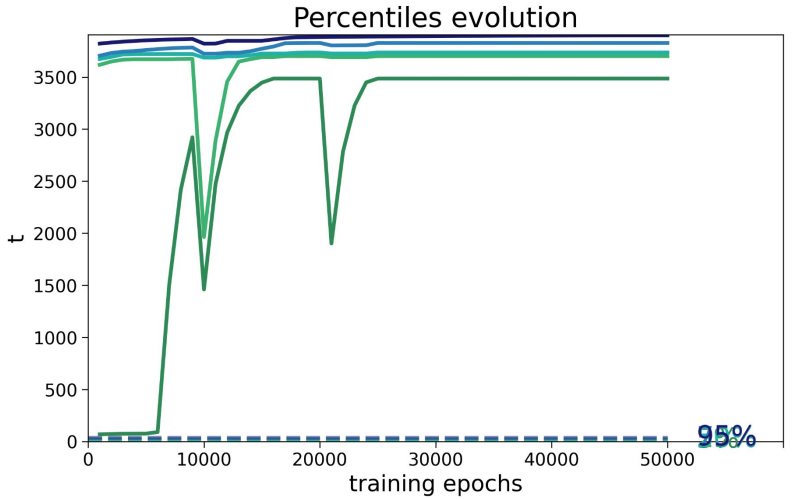

Cutting the angular feature θ

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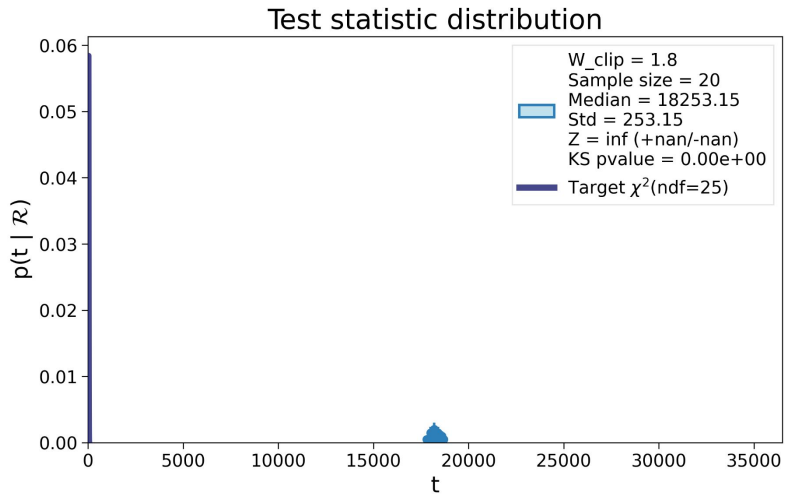

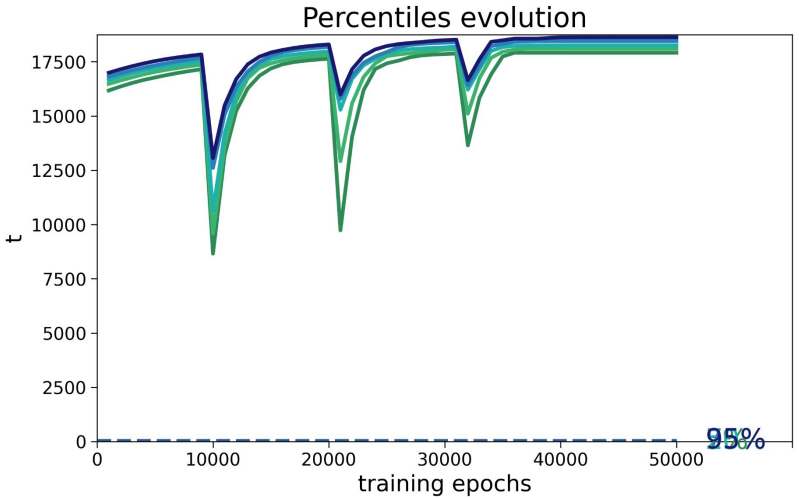

Cutting the angular feature θ

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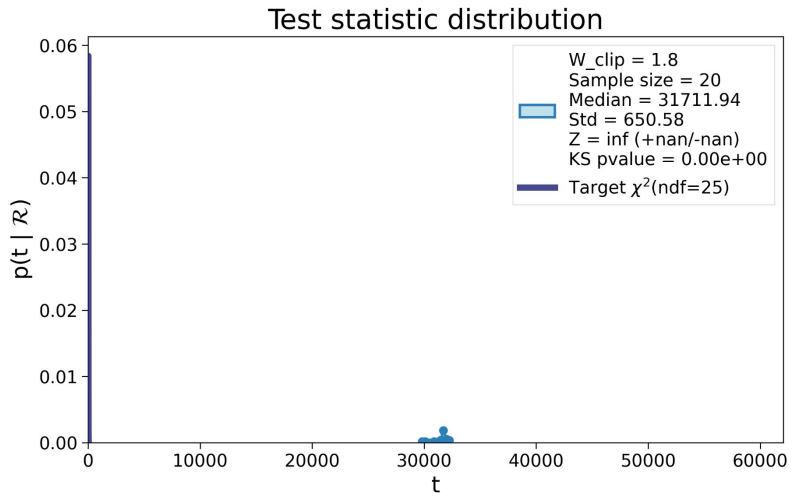
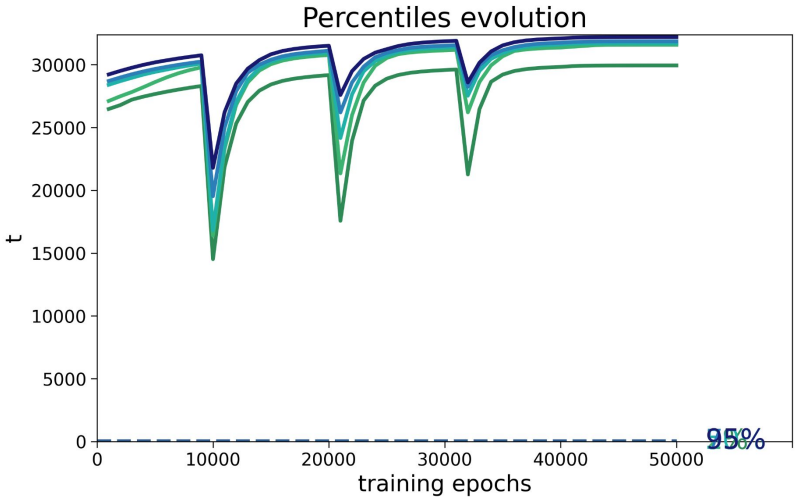




Summary of NPLM results

RUN 57:

- Anomaly detected without θ restrictions
- Anomaly detected with all θ restrictions
  - huge anomalies when
    - no small angles
    - no mid-to-large angles
  - similar to no θ restrictions when
    - no large angles

Summary of NPLM results

RUN 54 (reference):

- No anomaly detected without θ restrictions (by construction)
- Anomaly detected with all θ restrictions
  - huge anomalies when
    - no small angles
    - no mid-to-large angles
  - no anomalies with some discrepant test statistc
    - no large angles

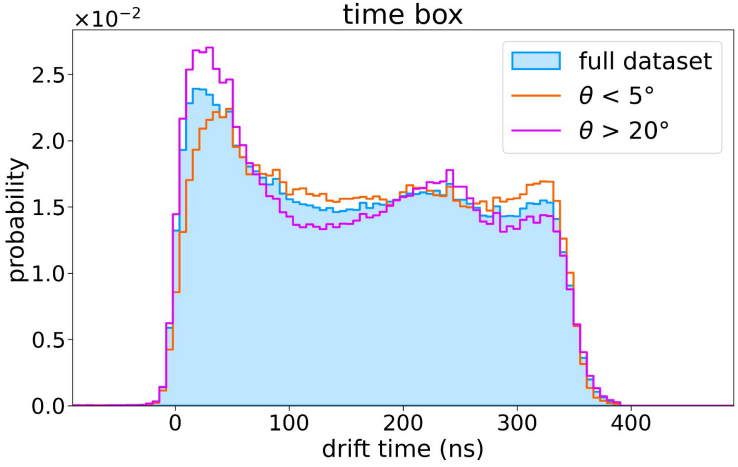
False positives and nuisance parameters

Type I errors in DQM:

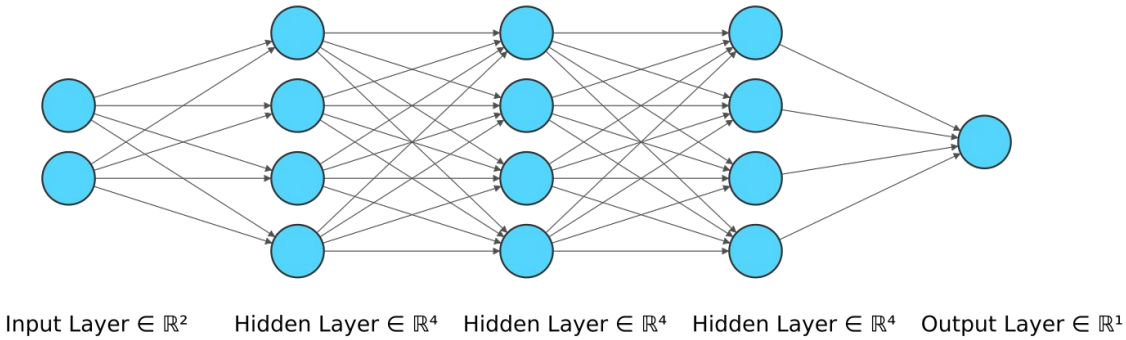
satisfactory run classified as discrepant

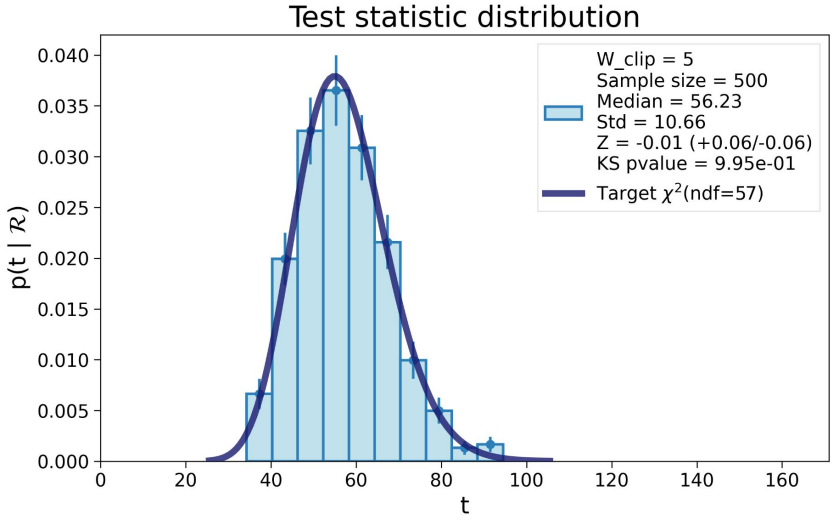
Example:

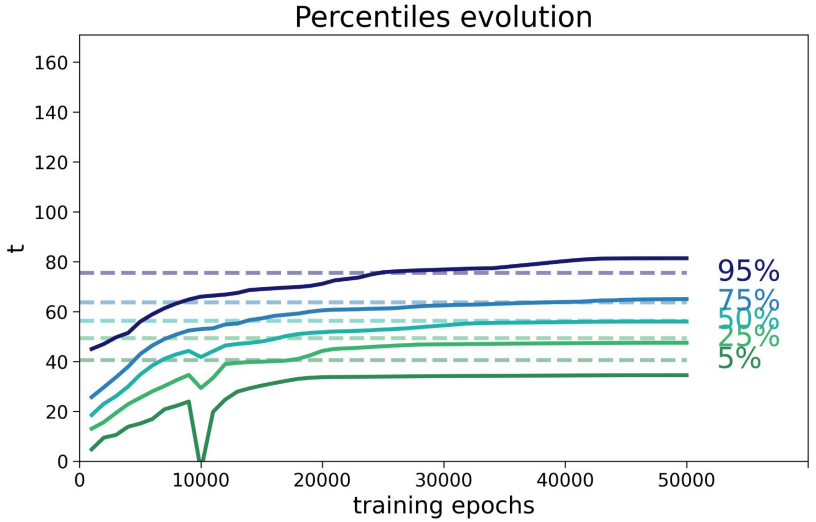
time box shape correlated with θ restrictions



More complex architecture test







NPLM output

Untouched datasets

Weight clipping = 5

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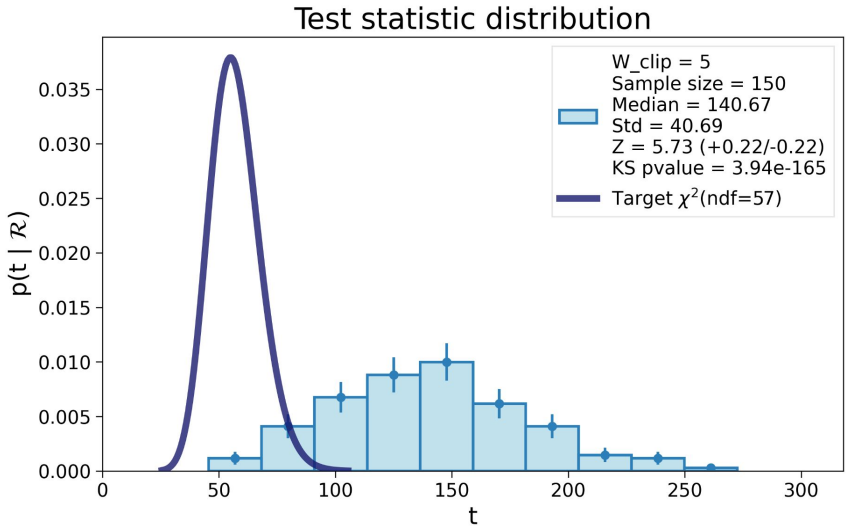
- N_{Data} = 5’000

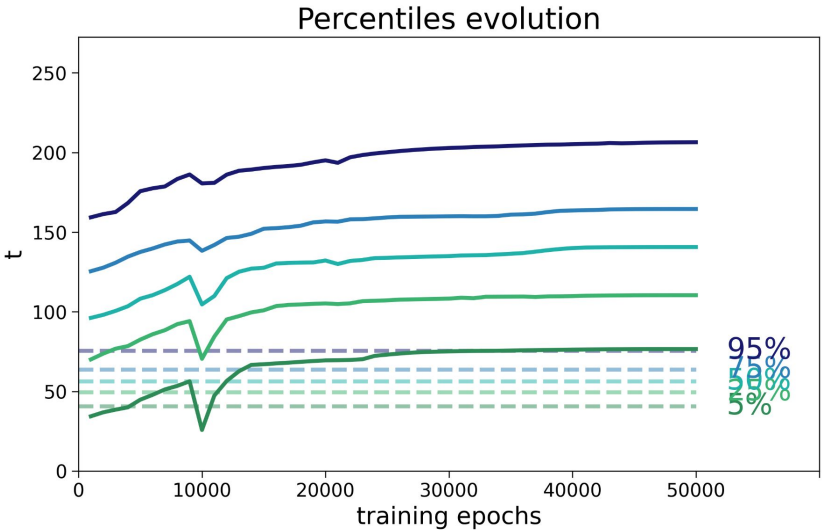
NPLM output

Untouched datasets

Weight clipping = 5

- $N_{Reference}$ = 200’000
- N_{Data} = 5’000





Conclusions

Summary

- Muon track reconstruction
- Memory and run time optimization
- Search for correlations
- NPLM application and tests on 2D datasets

Thank you for your attention